Connectedness of the African Equity Markets: A Time-Frequency Spillover Analysis

Abstract

This paper analyses return and volatility spillovers across the five largest and oldest African equity markets, namely: South Africa, Morocco, Egypt, Nigeria and Tunisia. The time-domain approach of Diebold and Yilmaz (2012) and the frequency-domain approach of Barunik and Khrehlik (2018) are employed to measure the spillovers empirically, in order to ascertain the nature and degree of interdependence within African stock markets. The findings suggest that these African equity markets' total return connectedness index is relatively moderate at an average of 9.7% over the full sample period between 11 January 2002 and 2 November 2018. However, the total volatility connectedness index is much higher at 19.9% on average, which is also larger than many other findings in the literature. These results suggest that South Africa and Egypt are usually the net transmitters of both return and volatility spillovers, while Morocco, Nigeria and Tunisia are usually the net receivers of these spillovers. A subsequent rolling window analysis is then used to show that both return and volatility interconnectivity has increased over time. There are also a number of spikes that occurred during periods of crisis, as these measures are particularly high during the global financial crisis of 2008 and 2009. To consider the robustness of these results, various different frequency windows have been used, where it is noted that although the central tenant of the above findings are present across all frequency windows, the exact measure for the degree of African equity market connectedness is contingent on the frequency under consideration.

Contents

1. Introduction

Fluctuations in asset prices pose both an opportunity and a risk to investors and speculators alike, in an interconnected technosystem known as the financial markets. These so called financial markets exist for more than simply the matching of buyers and sellers but also for the creation and preservation of wealth. In addition, financial markets can be big drivers of economic and social prosperity when they work well. However, the interdependence and connectedness of global markets may sometimes come at a cost. During crisis periods when history has shown that volatility spikes as a result of uncertainty, markets are found to exhibit contagion effects, which have severe economic consequences for broader society (Matsuki *et al.*, 2018). The economic trade off between the benefits of integration and the problems of contagion is a well-researched area in the field, even locally, with papers such as Collins and Biekpe (2003); Alagidede and Boako (2018), among others. Hence, this paper seeks to investigate the connectedness or "spillovers" across financial markets in Africa. The focus is specifically on the five largest and oldest equity markets on the contintent, namely: South Africa, Egypt, Morocco, Nigeria and Tunisia. Spillovers can be defined as the variation in one asset that is attributed to, or caused, by shocks to another asset (Diebold and Yilmaz, 2009).[1] Having knowledge or evidence of the nature of relationships among financial markets through the degree of their spillover or connectedness is useful for government authorities and both financial and non-financial firms to diversify their portfolios, hedge their strategies, and manage their risks (Hamori and Toyoshima, 2018).

Of all the African financial markets up until 2006, only two, Ghana and South Africa, were found to possess a significant bidirectional long-run relationship (Adjasi and Biekpe, 2006). This paper seeks to investigate the degree of African equity market integration and its evolution. This is achieved by calculating the linkages of the African markets and comparing their return and volatility transmissions by first estimating time-varying conditional correlations within a general autoregressive conditional heteroscedasticity (GARCH) framework, followed by a comparison of return and volatility spillovers under time-domain and frequency-domain measures. The Diebold and Yilmaz (2012) and Barunik and Khrehlik (2018) methods are used to calculate the time-domain and frequency-domain approaches, respectively.

Four key considerations are emphasised in this paper. First, how connected the African equity markets are, second, which countries were net receivers or net transmitters of these returns and volatility, third, the changes in the degree of connectedness over time, and lastly, whether the results are the same for both the Diebold and Yilmaz (2012) and Barunik and Khrehlik (2018) methods i.e. whether the results are robust. This paper is structured in the following

[1]Spillover and connectedness are used interchangeably in this paper but ultimately the measurement of the spillover is the tool with which to calculate the degree of connectedness.

way: section 1 continues with an overview of similar existing literature and a background on the African equity markets, section 2 describes the data and methodology that has been used in this study while presenting relevant descriptive statistics on the sample data, followed by section 3 which formally presents the models and their underlying principles. These models are estimated and their results are presented and discussed in section 4. Sections 5 and 6 conclude and suggest improvements and scope for future research in this area, respectively.

1.1. Review of the Existing Literature

The spillover effect can be explained in a number of ways: from an information transmission, flight-to-quality channel, or portfolio rebalancing perceptive. Considering the aforementioned importance of portfolio diversification to manage risk in the form of volatility, a popular area of research is the study of the degree of synchronisation between financial markets; be it cointegration of stock markets, spillovers in exchange rate volatility, causal links between two different asset classes, or inter-sector contagion effects, to mention but a few. The related market synchronisation literature review to follow will first outline relevant papers which employ GARCH modelling approaches, followed by studies involving spillover analyses implemented in the time-domain, frequency-domain or both.

There is considerable interest in the study of the transmission of returns and volatility among emerging capital markets and due to the convenient accuracy of GARCH models in modelling returns and volatility for most financial variables (general in-sample predictive accuracy), many studies have followed this approach in assessing the dynamic linkages between variables. For example, unidirectional volatility spillovers from equity markets to foreign exchange markets are found using a multivariate GARCH analysis in a South African context (Bonga-Bonga and Hoveni, 2013), as well as currency spillovers from the United states to West Africa using a multivariate BEKK-GARCH model (Emineke, 2016). Theodossiou and Lee (1993) study global developed equity market connectedness in detail, under a multivariate GARCH approach. The result is that most developed market volatility is “imported” from other developed markets, which is somewhat surprising. But when emerging markets are added to the sample, Worthington and Higgs (2004) find evidence of equity return spillovers of small magnitude from the developed to emerging markets and of large magnitude within the emerging markets. Also, own volatility persistence is found to be stronger than the cross-market volatility spillover. Chou *et al.* (1999) test the relationship in volatility between the Taiwanese and New York stock exchanges and find evidence supporting the conventional expectation that volatility spills over from the developed market in New York to the emerging market in Taiwan.

A more sparse area of research is the African case. Alagidede and Panagiotidis (2008) confirm that the stylised facts of volatility hold for the majority of countries in Africa. In a Sudanese study Ahmed and Suliman (2011) also suggest the stylised facts for this fragile country but that there are no equity volatility linkages to international markets. Using a VAR-EGARCH framework for equity markets in Ghana, Kenya, Nigeria and South Africa, Kuttu (2014) finds high persistence of own market volatility as well as a strong bidirectional connection between South Africa and Nigeria. For equity markets in the Chinese region, Mohammadi and Tan (2015) conclude that the United States is a net transmitter of spillovers for both return and volatility to the region but that there is no intra-regional spillover between Hong Kong and mainland China even though the market returns seem strongly correlated. The BRIC (Brazil, Russia, India and China) markets are also studied in a similar multivariate BEKK-GARCH context to find that India is the least integrated in the region when volatility is concerned, however strong linkages are found between the remaining countries.

The formal, post-GFC (global financial crisis), development of an econometric spillover measure in the time-domain context by Diebold and Yilmaz (2009) sparked even more research into the area of market dependency as a risk due to the financial market crash's adverse economic and societal effects. The calculation of a spillover index also allowed the transmission effects to be quantified in a convenient way for cross comparison. One of the drawbacks of this method was the inability to source or decompose the spillover. In other words, only total spillovers were calculated.[2] An update to include explicit directional spillovers was subsequently added to the measure in the publishing of Diebold and Yilmaz (2012), making this one of the most popular applications for measuring market connectedness.[3] An example of research using this methodology is that exchange rate spillovers increase during periods of crisis for currencies in African countries (Kavli and Kotze, 2012).

Barunik and Khrehlik (2018) extended upon the Diebold and Yilmaz (2012) spillover index using a spectral analysis to allow for the spillovers to be calculated at different frequencies. Even though the Barunik and Khrehlik (2018) paper is recent, numerous authors have been interested in the time-frequency dynamics of variable connections. Namely, Toyoshima and Hamori (2018); Ferrer *et al.* (2018); Barunik, Bevilacqua and Tunaru (2018); Barunik and Kocenda (2018); Trabelsi (2018) and Cunado *et al.* (2018) all make use of the Barunik and Khrehlik (2018) method in their analysis of various market linkages between asset class(es). Ferrer *et al.* (2018) focus on the link between renewable energy stocks and oil prices where Barunik and Kocenda (2018) study the connectedness of oil and forex markets but Barunik, Bevilacqua and Tunaru (2018) extend their scope even further by introducing an "asymmetric fear connectedness" measure to study the effect of investor expectations on the financial system in the United States. The most

[2]Spillovers to/from each market added to spillovers to/from all other markets. This will be clarified in section 3.2.

[3]Spillovers to/from a particular market. This will be clarified in section 3.2.

modern application of the Barunik and Khrehlik (2018) method is by Trabelsi (2018) which studies volatility spillover of widely traded asset classes with the addition of cryptocurrencies. Cunado *et al.* (2018) authors another paper which looks at the spillover of inflation in selected Euro-area countries. The only article which considers the spillovers from both return and volatility, is Toyoshima and Hamori (2018). But, their focus is on global oil markets instead of equities as in this paper. This is a gap which this paper fills in the existing literature. To the knowledge of the author, this is the first paper to analyse returns *and* volatility of the African markets, focusing solely on the equity market, using GARCH modelling techniques which are extended to include and compare spillovers across the time and frequency domain measures.

To summarise the common themes throughout the literature; aggregate same sector co-movement is amplified during periods of heightened global economic uncertainty, directional spillover is contingent on regional income levels, transmitters and receivers of volatility depend on the frequency under consideration and that market connectedness is heightened in the short-term. Sparse time-frequency research has been done on the African markets in general, but this is drastically changing as the world becomes more interconnected and timeous demand for information amplifies.

1.2. Background on the African Equity Markets

The establishment of stock markets in the region extends as far back in history as the 19^{th} century. It can be seen in Table 1, presented on the following page, that Egypt has the oldest stock market in Africa – the Alexandria Stock Exchange. This exchange was established in 1883, followed by the Cairo Stock Exchange which opened in 1903. Similarly, the Johannesburg Stock Exchange (JSE) in South Africa came to market soon after in 1887 and the Casablanca Stock Exchange in 1929 (African Securities Exchanges Association, 2018).

Further development of the continent's capital markets led to the more recent establishment of the Nigerian and Tunisian exchanges in 1960 and 1969, respectively. Most notably in Table 1 the JSE is a standout when trading volume and market capitalisation are concerned, even with only a slightly higher amount of listed companies which indicates that the exchange consists of some large cap stocks since only 301 companies are valued at 279% of their GDP. For the other four markets there is a large variation in the number of companies listed on each exchange and their market capitalisations, which indicates a fair amount of dissimilarity where exchanged establishment (not age) is concerned. As Table 1 also insinuates, trading volumes are very low compared to developed markets. This emphasises one of the barriers to doing business in the markets as they are quite illiquid (with the exception of South Africa). The lack of liquidity could deter investors because the securities cannot easily be sold or exchanged for cash without a substantial loss in value. Illiquid assets can largely be ascribed to inefficient infrastructure where examples could include; the poor pricing of markets, lack of digitisation and high trading costs.[4]

Table 1: Market activity of the African stock exchanges

Country	Exchange	Date exchange opened	Number of listed companies	Trading volume (US$ million)	Market capitalisation in US$ billion (% of GDP)
South Africa	Johannesburg Stock Exchange	1887	301	34636	987 (279)
Nigeria	Nigerian Stock Exchange	1960	176	178	32 (9)
Egypt	Egyptian Stock Exchange	1883	222	1040	41 (17)
Morocco	Casablanca Stock Exchange	1929	75	506	57 (56)
Tunisia	Tunis Stock Exchange	1969	20	28	9 (22)

[a] Source: African Security Exchanges Association (2018)

2. Data and Methodology

2.1. Data

The data in this study consists of weekly US dollar denominated equity index prices over the sample period of 11 January 2002 to 2 November 2018 for the five largest and oldest equity markets in Africa. As this study considers changes that have arisen over time, the GFC is purposefully included in the sample so that one could consider the potential effect of this event on connected markets on a continent and in turn, broader society. These prices are value-weighted closing prices of the JSE All Share (South Africa), NSE All Share (Nigeria), CASE 30 (Egypt), MASI (Morocco) and TUNINDEX (Tunisia) which are sourced from Thomson

[4]This paper is not suggesting that the age of a stock market be correlated to its market capitalisation, nor has substantial evidence hereof been found. Instead, the largest exchanges on the continent were merely chosen as the sample.

Reuters Datastream. These five stock markets sampled account for over approximately 70% of equity market capitalisation in Africa and the indices represent 85% of stocks traded in the equity markets of the measured countries. In addition, using an individual country index is a widely employed data measure in the literature on equity market co-movements and volatility transmission effects. It should also be noted that of the five countries in question, only two (South Africa and Nigeria) are not regionally integrated, and as such the degree of connectedness could be expected to be relatively high, provided that South Africa and Nigeria are not dominant in this system.

The variable of interest is the weekly return on the equity indices. This is to ensure that the series used for modelling are stationary, as the indices contain unit roots.[5, 6] The data are converted into weekly returns by subtracting the logarithm of the previous week's price from the logarithm of the current week's price.

$$r_t = \log\left(\frac{p_t}{p_{t-1}}\right), r_t^2 = \left[\log\left(\frac{p_t}{p_{t-1}}\right)\right]^2 \tag{1}$$

where r_t is a return approximation, r_t^2 is a volatility approximation and p_t is the US dollar price in week t.

Even though daily data is most popular throughout the literature, the choice to use a weekly frequency as in Diebold and Yilmaz (2009), was motivated by more recent articles – daily data has been criticised of suffering from too much noise, non-synchronous trading and the day-of-the-week effect (Arouri, Jouini and Nguyen, 2012). Using weekly data also simplifies the mean equation to a scalar as no explanatory or dummy variables for a weekend are necessary since the price on the same day of each week is used.[7] There is a trade off between a high number of observations over a shorter time span to a slightly lower number of observations over a longer time span. The latter is more appropriate for this study as strong autoregressive conditional heteroscedasticity (ARCH) effects are still observed when using data that is measured at this frequency.

[5] This paper uses a different analysis to Barunik and Khrehlik (2018); using stationary modelling techniques on stationary data instead of non-stationary modelling techniques on non-stationary data.

[6] See the Appendix for stationarity tests.

[7] Weekly data is especially helpful because the equity indices of interest relate to multiple countries that are classified in multiple time zones, which would pose as problematic for daily data.

2.2. Methodology

The modelling techniques used in this paper have been carefully considered and selected to suit the problem at hand. Although a few authors in this field have made use of similar methods, the reasoning pertaining to the use of the combination of econometric methods in this article is explored here.

The initial model, the asymmetric multivariate GARCH, is positioned as the baseline volatility model of the data as it encompasses known stylised facts on volatility i.e. it suits the properties seen in the data. It allows one to measure if significant (uni or bi-directional) spillover relationships exist in the data. These relationships, if any, can subsequently be retested using the time-frequency domain analysis. A time-domain analysis has been selected as one of the two main methods to answer the research question as its results provide information regarding the value of a spillover at any given instance. The decision to expand into the inclusion of the frequency-domain analysis is to determine the stability of the system, as part of the research question aims to measure the change in spillover across selected African markets *over time*. This is achieved by decomposing spillovers into frequencies to measure the rate at which the spillover is varying.

In summary, utilising a time-frequency domain analysis of spillovers is the most modern and convenient way of testing spillovers of this nature . These methods produce one number, interpreted as a percentage, which represents the amount transferred across variables - allowing for ease of comparison across markets and even the results of other academic articles in this field.

2.3. Descriptive Statistics

In this section a selected number of tables and figures will be presented and discussed in order for the reader to gain an initial understanding of the underlying variables and the way each variable behaves separately, while graphically observing any similarities or differences, prior to the formal modelling and testing for spillover effects or relationships. The descriptive statistics presented include; time plots of the respective equity returns and their volatility, a selection of return and volatility summary statistics and correlation matrices of the five indices in question.

Figure 1. South African Equity Returns

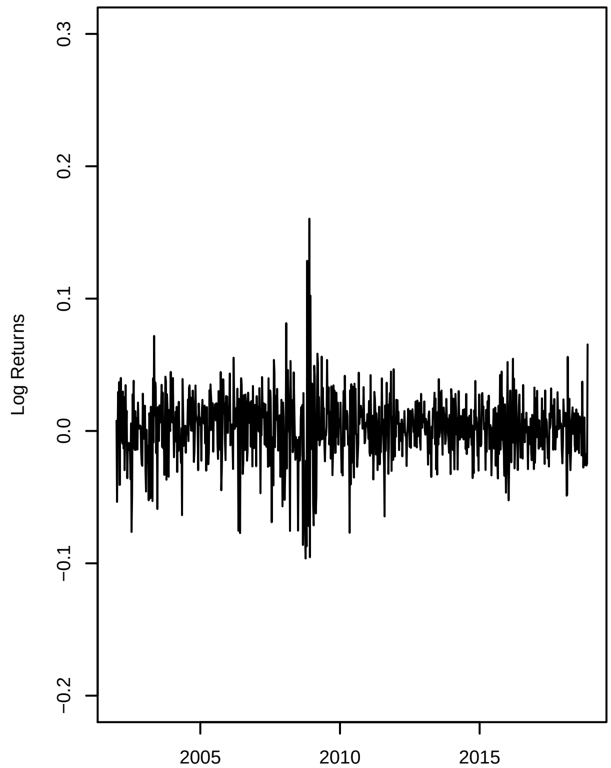


Figure 2. Volatility of South African Equity Returns

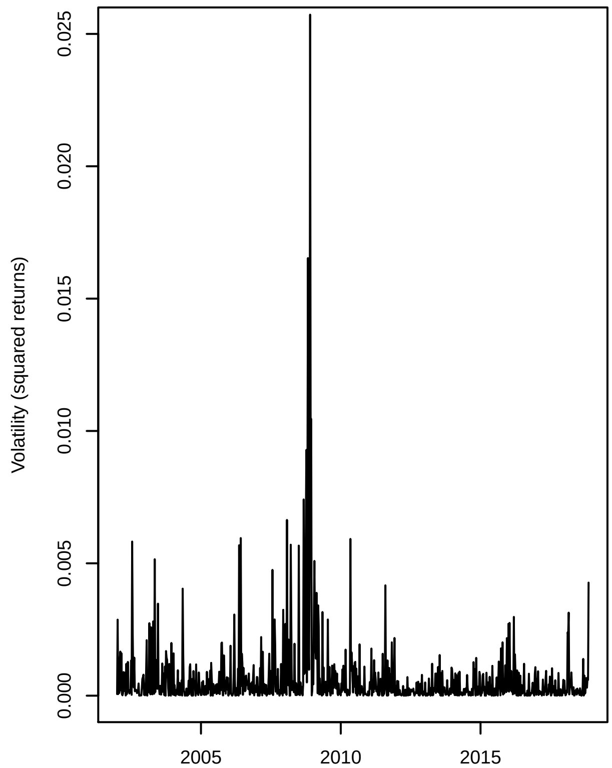


Figure 3. Nigerian Equity Returns

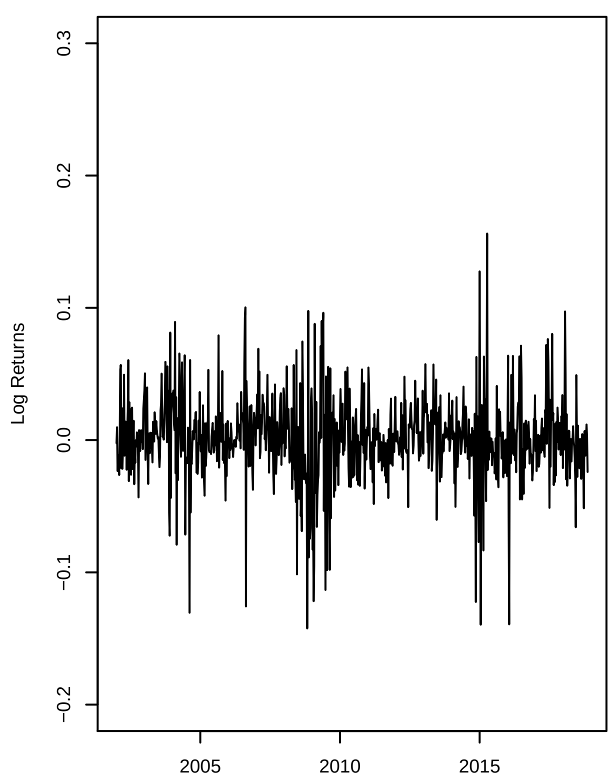


Figure 4. Volatility of Nigerian Equity Returns

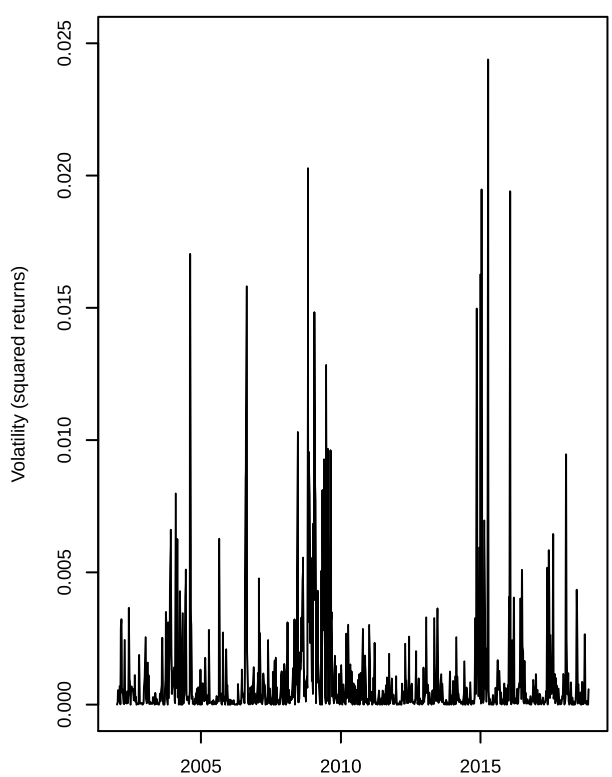


Figure 5. Egyptian Equity Returns

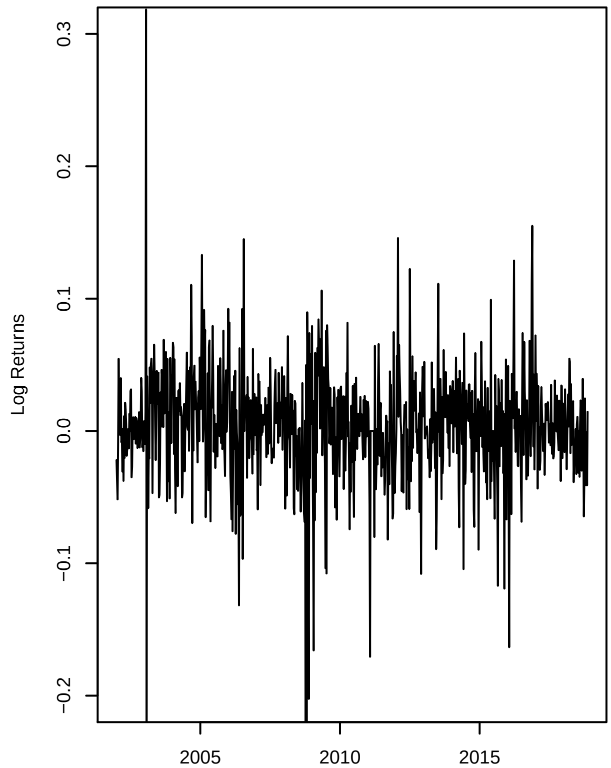


Figure 6. Volatility of Egyptian Equity Returns

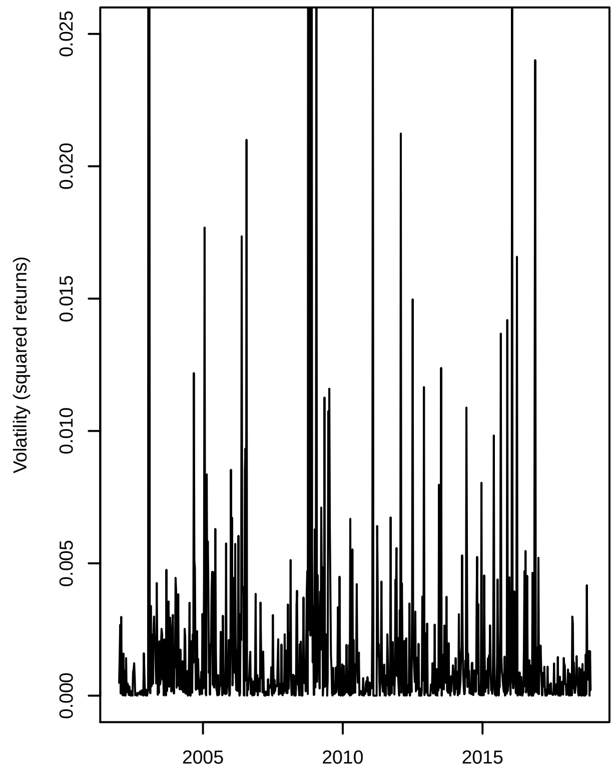


Figure 7. Moroccan Equity Returns

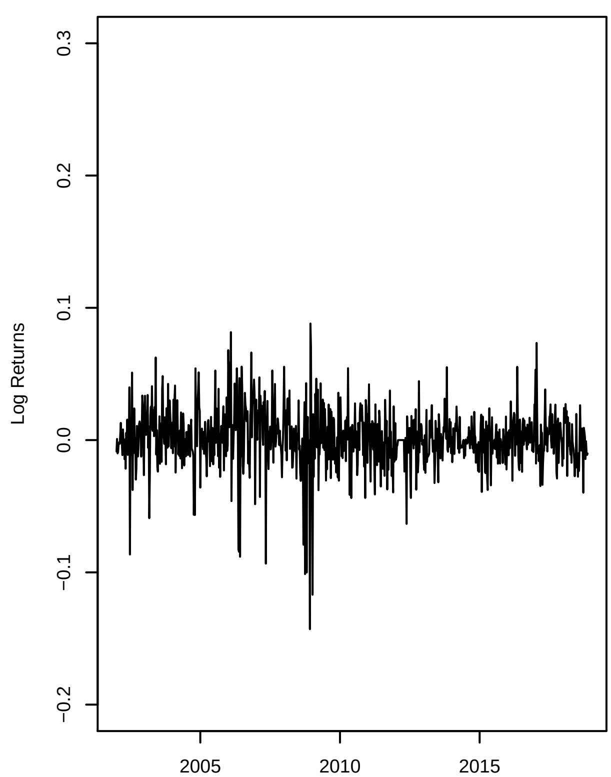


Figure 8. Volatility of Moroccan Equity Returns

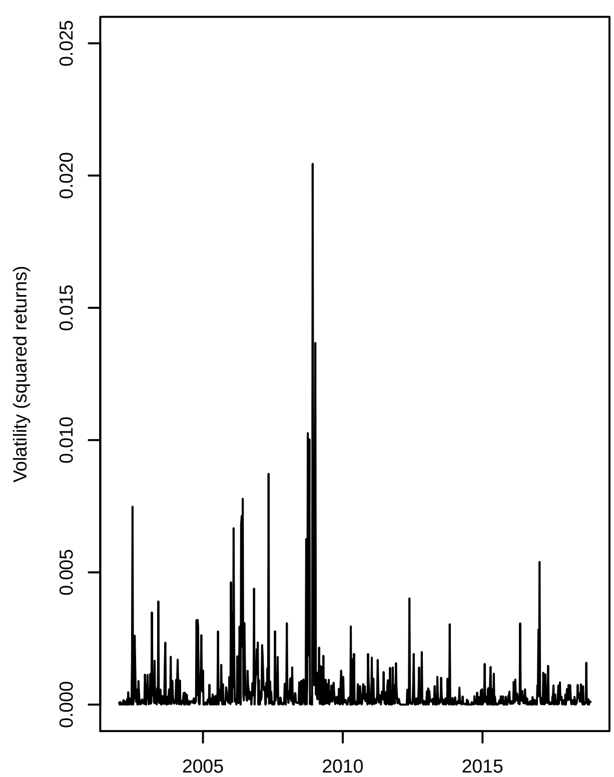


Figure 9. Tunisian Equity Returns

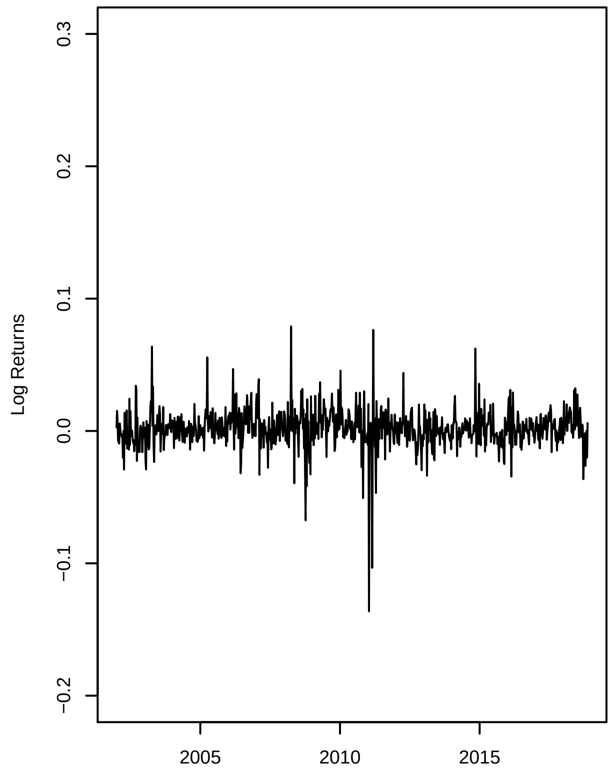
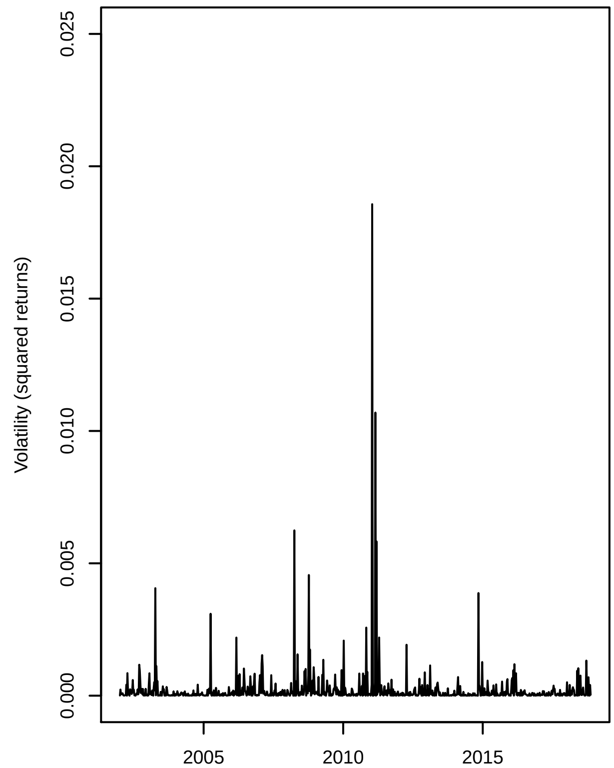


Figure 10. Volatility of Tunisian Equity Returns



The main conclusion of Figures 1 to 10 which have been presented above, is the evidence of volatility clustering, where large movements are followed by movements of a similar magnitude, while small movements are also often followed by movements that are relatively benign.[8] Volatility clustering is common to financial time series variables. It also appears that in a financial crisis the negative return shocks have higher volatility than positive return shocks. The clustering is not more pronounced for a specific country but the distributional properties in the return series seem to be non-normal, but will be formally checked in the tables of summary statistics to follow.

The summary statistics presented in Table 3 and 4 are helpful in quantitatively grasping the movements of the equity markets in the sample period. Most notably, the Egyptian markets have significantly outperformed their counterparts with an average return of 19% and high of 32% per annum. In turn, Egyptian equities are by far the most risky with the largest standard deviation (and mean volatility) by a long way at 1.1089 (9.5%). The lowest performing sample equity asset class was that of Nigeria: Nigerian equities yielded average per annum returns of only 6% across the sample period.

[8]Figures 1 to 10 are presented using the same axes for the returns of a market and the same axes for the volatility of a market for ease of comparison.

Table 2: Summary statistics of weekly equity returns from January 2002 - November 2018

	South Africa	Nigeria	Egypt	Morocco	Tunisia
Mean	0.0954	0.0638	0.1924	0.0793	0.1046
Median	0.003	0.0014	0.0055	5e-04	0.0017
Maximum	0.1604	0.1562	0.3184	0.0881	0.079
Minimum	-0.0963	-0.1424	-0.2511	-0.143	-0.1363
Std Dev	0.6479	0.8199	1.1089	0.5853	0.3758
Skewness	-0.026	-0.297	-0.4086	-0.7113	-1.0701
Kurtosis	3.6661	3.6986	7.8093	4.9972	15.3264
ARCH					
Jarque-Bera	491.7996	513.3619	2255.4799	987.5874	8760.9231
p-value	0	0	0	0	0
Normality					
Shapiro-Wilk	0.96	0.9424	0.9192	0.9375	0.8752
p-value	0	0	0	0	0
Obs	878	878	878	878	878

[a] Mean and standard deviation have been annualised.

Table 3: Summary statistics of weekly equity volatility from January 2002 - November 2018

	South Africa	Nigeria	Egypt	Morocco	Tunisia
Mean	0.0324	0.0517	0.0952	0.0264	0.0111
Median	2e-04	2e-04	5e-04	1e-04	0
Maximum	0.0257	0.0244	0.1014	0.0204	0.0186
Minimum	0	0	0	0	0
Std Dev	0.0385	0.0615	0.1472	0.0344	0.0223
Skewness	8.6996	5.1822	10.3223	7.5675	14.5582
Kurtosis	115.0177	33.6689	141.5752	81.3521	270.7192
Jarque-Bera	495038.4574	45400.5703	748851.3439	250494.5694	2712164.9191
p-value	0	0	0	0	0
Normality					
Shapiro-Wilk	0.3792	0.429	0.2762	0.3638	0.1942
p-value	0	0	0	0	0
Obs	878	878	878	878	878

[a] Mean and standard deviation have been annualised.

The Tunisian equity market seemed to be the most stable with the lowest risk (standard deviation of 0.3758) per unit of return (mean of 10.4%). All five markets are negatively skewed, indicating that negative returns are more common than positive returns over the time period. Kurtosis compares the distribution of the series to the normal distribution, and therefore cannot reliably

Table 4: Correlation matrix of returns from January 2002 - November 2018

	South Africa	Nigeria	Egypt	Morocco	Tunisia
South Africa	1.0000	0.0170	0.3018	0.1865	0.0432
Nigeria	0.0170	1.0000	0.1049	0.0933	-0.0368
Egypt	0.3018	0.1049	1.0000	0.1777	0.0967
Morocco	0.1865	0.0933	0.1777	1.0000	0.0713
Tunisia	0.0432	-0.0368	0.0967	0.0713	1.0000

Table 5: Correlation matrix of volatility from January 2002 - November 2018

	South Africa	Nigeria	Egypt	Morocco	Tunisia
South Africa	1.0000	0.1783	0.2295	0.2607	0.0647
Nigeria	0.1783	1.0000	0.1150	0.0465	0.0064
Egypt	0.2295	0.1150	1.0000	0.1063	0.0852
Morocco	0.2607	0.0465	0.1063	1.0000	0.0614
Tunisia	0.0647	0.0064	0.0852	0.0614	1.0000

be compared across the two series as they have a differing variance. What one can conclude is that both variables are leptokurtic (kurtosis greater than 3) i.e. have fat tails. The Jarque-Bera and Shapiro-Wilk statistics, included in Table 2 and 3, use skewness and kurtosis to test whether the returns and volatilty of stocks are normally distributed. The tests both reject the null hypothesis that the returns are well approximated by the normal distribution for all cases and the evidence from the return plots suggest that it may be worth modelling volatility with a GARCH model. Therefore, a GARCH modelling is employed initially to set the scene for a spillover measure which along with the rolling window analysis to follow will investigate the aim of this paper.

3. Econometric Model

3.1. Asymmetric Multivariate GARCH Model

Globalisation has resulted in the financial markets being more dependent on each other than ever before (Trabelsi, 2018). Consequently, knowing how the markets are interrelated is of great importance in financial analysis and forecasting. Volatility can generally be defined as the degree of fluctuation in asset prices. When building a volatility model, it should incorporate some stylised facts: pronounced persistence, mean-reversion and asymmetry (Engle and Patton, 2001). In order to provide useful insight into the research question – to see whether there are spillovers within the African equity markets – an extention to the vanilla GARCH model is presented. One of the most widely used multivariate conditional covariance models is the BEKK (Baba, Engle, Kraft and Kroner) as developed in Engle and Kroner (1995). The model requires the imposition of parameter constraints on the Hessian matrix to ensure a positive definite conditional variance-covariance matrix (H_t). A five-variable asymmetric GARCH model is considered in this case, which allows for the answering of part of the research question: the interdependence across the continent's equity markets through the second moment. This multivariate GARCH approach is performed in the asymmetric BEKK style as in Emenike (2016) which studies the spillover effects of exchange rate volatility in West Africa.

Unfortunately, the multivariate BEKK model can only be estimated by imposing specific restrictions on the conditional variance-covariance matrix e.g. positive definiteness of H_t. To circumvent this problem, Engle and Kroner (2002) proposed a quadratic formulation for the parameters which became known as the BEKK model (Brooks *et al.*, 2003). This formulation takes quadratic expressions for each of the terms and forces them all to be positive (volatility is always positive). One of its drawbacks is that the number of parameters grows linearly with the number of return series. Since only the first order case is necessary for this study (GARCH(1,1) instead of a higher order GARCH), this model is sufficient because the linear growth of terms is not applicable. Although there are quite a few parameters to estimate, this model allows for the effect from other variables: transmission of returns and volatility. Now, the model based on the multivariate BEKK-GARCH(1,1) representation proposed by Engle and Krone (1995) is outlined below:

$$R_t = \mu + AR_{t-1} + \epsilon_t, \epsilon_t \mid I_{t-1} \sim \mathcal{N}(0, H_t) \tag{2}$$

Equation (2) is the mean equation which is modelled as an autoregressive process, because in this specification the underlying process (share prices) typically exhibits a certain degree of persistence. μ is a 5 x 1 vector of constants, R_t is a 5 x 1 vector of weekly returns at time t and A is a 5 x 5 matrix of parameters associated with the one-period lagged returns. The error term, ϵ_t, is white noise with a non-zero variance-covariance matrix. The diagonal elements in matrix A, A_{ij}, where i denotes the row index and j the column index, measure the effect of own past returns. ϵ_t is the 5 x 1 vector of random errors for the model which evolves normally, conditional on a prior information (I_{t-1}), with mean 0 and corresponding 5 x 5 conditional variance-covariance matrix H_t. This multivariate structure thus facilitates the measurement of the effects of innovations in the mean stock returns of one series on its own lagged returns and those of the lagged returns of other markets.

The following formulation of H_t ensures that the number of parameters to be estimated are much lower, and that the conditional variance-covariance matrix (H_t) is positive definite.

$$H_t = B'B + C'\epsilon_t\epsilon_{t-1}C + D'H_{t-1}D \tag{3}$$

The asymmetry of volatility is introduced by replacing equation (3) with equation (4). This amendment allows for the asymmetric responses of volatility, i.e. stock volatility tends to rise more in response to negative shocks (bad news) than positive shocks (good news).

$$H_t = B'B + C'\epsilon_t\epsilon_{t-1}C + D'H_{t-1}D + E'\gamma_{t-1}^{'}\gamma_{t-1}E \tag{4}$$

where γ_t is defined as 1 if ϵ_t is negative and zero otherwise, as below. This specification allows for negative shocks to have a larger effect than positive shocks.

$$\gamma_{t-1} = \begin{cases} 1 & \text{if } \epsilon_t < 0 \\ 0 & \text{if } \epsilon_t \geq 0 \end{cases}$$

Where matrix B is a 5 x 5 lower triangular matrix of constants. The diagonal parameters in matrices C and D represent the effect of own past shocks and past volatility of market i on its conditional variance, while the diagonal parameters in matrix E, E_{ij} where $j = i$, measure the response of market i to its own past negative shocks. The off-diagonal parameters in matrices C and D, C_{ij} and D_{ij} where $j \neq i$, measure the cross-market effects in volatility, also known as volatility spillover. The off-diagonal parameters in matrix E, E_{ij} where $j \neq i$, measure the response of market i to the negative shocks of other markets, termed the cross-market asymmetric responses. In order to answer or provide insight on the research question, the matrices of interest are A, D (since C is similar to D) and E.

3.2. Formal Method for the Calculation of Spillovers

In economics, spillovers refer to a type of network effect which occur when events or price movements in one market have repurcussions in another market. Diebold and Yilmaz (2009) define them as the variation in one asset that is attributed to, or caused, by shocks to another asset.[9] Futhermore, in this paper's context the purpose of calculating spillovers is to calculate the degree of African financial market connectedness, which encompasses both definitions of spillovers. Put simply, whether the markets in question are dependent, independent or mutually exclusive and whether the relation differs at different periods. As a rule of thumb, the higher the

[9] A recent example is the 2018 currency crisis in Turkey causing a frantic emerging market sell off. African markets had to bear the consequences even though no other African countries were directly involved (Lee, 2018).

spillover (regardless of sign) the stronger the relationship between markets, in addition, the sign of the spillover informs the reader if a country is a net receiver (positive sign i.e. receives more than it transmits) or net transmitter (negative sign i.e. transmits more than it receives) of return or volatility spillovers where no spillover indicates an independent relationship. What is of key interest to the author is whether the (lack of) spillover is as a result of market connectedness or if it is simply an externality effect. This is tested using the frequency-domain analysis. To describe the exact specification details, firstly, in section 3.2.1. the Diebold-Yilmaz (2012) generalised forecast error variance decomposition (GFEVD) time-domain method will be introduced. To build on this measure; secondly, section 3.2.2. outlines the Barunik and Khrehlik (2018) method which extends on the previous method by decomposing the spillovers into different frequencies to determine whether time periods affect spillovers.

3.2.1. Time-domain analysis

In the time-domain analysis, the method below will be followed in order to reach a measure of connectedness which can be applied to the data. Firstly, in order to measure the transmission effect, return or volatility series coefficients are initially estimated using a vector autoregressive (VAR) approximating model. The variance decomposition matrix of this model is subsequently used to calculate the spillover for each time period, added together.[10] The following model measures spillovers without frequency bands: a standard Diebold-Yilmaz (2012) calculation method. A VAR model of order p is fitted to the stationary endogenous equity return or volatility series, X_t, at every $t = 1, ..., T$ as follows:

$$X_t = K + \phi_1 X_{t-1} + \phi_2 X_{t-2} + ... + \phi_p X_{t-p} + \epsilon_t, \epsilon_t \sim N(0, \sum) \tag{5}$$

Where K is a 5 x 1 vector of the constants, $X_t = (x_{t,1}, ..., x_{t,5})'$ is a vector of the same dimensions at time t, $(\phi_1, ..., \phi_p)$ represents the coefficient matrices of dimension 5 x 5. These matrices contain complete information about the interaction effects between all the variables since each is regressed on its own lags as well as the lags of the others. The error term, ϵ_t, is has the same properties as in the GARCH model which ensures information transmission effects. The VAR model can be simplified to:

$$\Phi(L)X_t = \epsilon_t \tag{6}$$

where, by matrix manipulation, the moving average MA(∞) representation is given by:

[10] VAR decompositions measure how much of the H-step ahead forecast error variance of some variable i is due to innovations in another variable j. This process was originally developed by Sims (1980).

$$X_t = \Psi(L)\epsilon_t \tag{7}$$

where $\Psi(L) = [\Phi(L)]^{-1}$ which is a matrix of infinite lag polynomials, assuming that its roots, $|\Phi(z)|$, lie outside the unit circle (i.e. the system is covariance stationary as the eigenvalues are within the unit circle). Since $\Psi(L)$ contains an infinite number of lags it needs to be approximated by the MA coefficients, Ψ_h, at $h = 1, ..., H$ horizons. The connectedness measures rely on variance decompositions, which are transformations of these coefficients and allow the measurement of the contribution of shocks to the system of equations in this preliminary model. Cholesky's decomposition of the variance-covariance matrix $\sum$ is necessary because shocks do not appear singularly and need to be identified for their contribution to be measured. The GFEVD (invariant to ordering) can be written as given in Diebold and Yilmaz (2012) as:

$$(\Theta_H)_{j,k} = \frac{\sigma_{kk}^{-1} \sum_{h=0}^{H} \left[(\Psi_h \sum_{j,k})^2 \right]}{\sum_{h=0}^{H} \left(\Psi_h \sum \Psi_h' \right)_{j,j}} \tag{8}$$

where Ψ_h is the N x N matrix of moving average coefficients at lag h as defined earlier. Also, $\sigma_{kk} = (\sum)_{k,k}$ and $(\Theta_H)_{j,k}$ denotes the contribution of variable k to (the variance of the forecast error of the) element j at horizon h. The variance decomposition matrix $(\Theta_H)_{j,k}$ has to be normalised by its row sum.[11]

$$(\tilde{\Theta}_H)_{j,k} = \frac{(\Theta_H)_{j,k}}{\sum_{k=1}^{N} (\Theta_H)_{j,k}} \tag{9}$$

in equation (9) above, $(\tilde{\Theta}_H)_{j,k}$ measures the pairwise contribution from variable j to variable i at horizon H.

The main connectedness measure C_H is calculated according to the following formula:

$$C_H = 100 \left[\frac{\sum_{j \neq k} (\tilde{\Theta}_H)_{j,k}}{\sum \tilde{\Theta}_H} \right] = 100 \left[1 - \frac{Tr\left(\tilde{\Theta}_H\right)}{\sum \tilde{\Theta}_H} \right] \tag{10}$$

Equation (10)[12] measures the degree of connectedness. This equation simply measures the share of variances in the forecasts contributed by the errors (excluding own errors) or, as "the ratio of the sum of the off-diagonal elements to the sum of the entire decomposition matrix" (Diebold and Yilmaz, 2012).

[11] This normalisation is performed because the rows to the variance decomposition matrix Θ_H do not necessarily sum to 1.

[12] "Tr" represents the trace of a matrix and the multiplication by 100 is in order to interpret the results in percentage form.

3.2.2. Frequency-domain analysis

In order to delve into the overall measure of connectedness and study the transmission effects for different time periods (frequencies), a frequency-domain measure is required. This involves using a connectedness measure which calculates spillover for a certain frequency chosen by the researcher. Barunik and Khrehlik (2018) developed a measure which conveniently extends the Diebold and Yilmaz (2012) method: allowing for cross comparison of the spillovers, given that they are calculated according to the same underlying forumlas. The Barunik and Khrehlik (2018) method is simply a breakdown of the spillovers calculated by the Diebold and Yilmaz (2012) method – to decompose the specific spillover behaviour over selected time increments. This method can be classified as more modern as it provides a seamless link between high frequency data and a frequency model which can be used to extract useful economic information (in this case the connectedness of the markets in question). This frequency model simply requires the data input and after technical calculation, returns, in percentage form, the connectedness tables.

When measuring the spillovers per frequency (short, short to medium, medium to long and long-term), a frequency response function is necessary. This frequency response function is given by: $\Psi(e^{-iw}) = \sum_h e^{iwh}\Psi_h$.[13] This function is obtained from a Fourier transformation of the previous estimated MA coefficients Ψ_h. As derived by Diebold and Yilmaz (2012), the spectrum over frequencies $\omega \in (-\pi, \pi)$ is defined generally as:

$$[f(\omega)]_{j,k} \equiv \frac{\sigma_{kk}^{-1}|[\Psi(e^{-iw})\sum]_{j,k}|^2}{[\Psi(e^{-iw})\sum\Psi'(e^{iw})]_{j,j}} \tag{11}$$

where $\Psi(e^{-iw}) = \sum_h e^{-iwh}\Psi_h$ is the Fourier transformation of the impulse response Ψ_h and $[f(\omega)]_{j,k}$ denotes the portion of the spectrum of the j-th variable under the chosen frequency ω due to movements as a result of the k^{th} variable shocks. As the denominator in equation (11) represents the spectrum of the j^{th} variable (the diagonal element of the cross-density of X_t) under a chosen frequency ω, the whole term can thus be interpreted as the *quantity within the frequency causation* i.e. the spillover within this frequency band. To obtain a natural decomposition of original GFEVD to frequencies, $[f(\omega)]_{j,k}$ can be "weighted" by the frequency share of the variance of the j-th variable. This weighting function is defined as:

$$\Gamma_j(\omega) = \frac{\left[\Psi(e^{-iw})\sum\Psi'^{(e+iw)}\right]_{j,j}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}\left[\Psi(e^{-i\lambda})\sum\Psi'^{(e+i\lambda)}\right]_{j,j}d\lambda} \tag{12}$$

Equation (12) represents the power of the j-th variable at a given frequency ω, which adds

[13] In this case i is not an indexing parameter but a representation of the imaginary component i.e. $i = \sqrt{-1}$, ω is the frequency and h represents the horizon.

across all frequency values of ω to reach the constant value of 2π which completes the band. The reader should note that although the Fourier transformation of the impulse response is generally a complex numerical value or term, so to obtain a real number for inference (through the generalised causation spectrum) the absolute value of the coefficients of the weighted complex numbers or terms are squared. This squaring function ensures that a real number is produced.

Next is to formally introduce the procedure of incorporating the size of certain frequency bands.[14] A frequency band is given as $d = (a, b) : a, b \in (-\pi, \pi), a < b$ and the generalised variance decompositions on frequency band d are:

$$(\Theta_d)_{j,k} = \frac{1}{2\pi} \int_d \Gamma_j(\omega) \left[f(\omega)\right]_{j,k} d\omega \tag{13}$$

As shown, it is relatively straightforward to define connectedness measures on a given frequency band when applying the spectral representation of GFEVD. Now, the *scaled* GFEVD on band d (as defined previously) is $\tilde{\Theta}_d$ as follows:

$$(\tilde{\Theta}_d)_{j,k} = \frac{(\Theta_d)_{j,k}}{\sum_k (\Theta_\infty)_{j,k}} \tag{14}$$

Next, to simplify the algebra, connectedness "within" each band d is defined as:

$$C_d^W = 100 \left[1 - \frac{Tr(\tilde{\Theta}_d)}{\sum \tilde{\Theta}_d}\right] \tag{15}$$

and the "within" connectedness C_d^W is incorporated in the measure of total frequency connectedness within each band (Barunik and Khrehlik, 2018).

$$C_d^F = 100 \left[\frac{\sum \tilde{\Theta}_d}{\sum \tilde{\Theta}_\infty} - \frac{Tr(\tilde{\Theta}_d)}{\sum \tilde{\Theta}_\infty}\right] = C_d^W \frac{\sum \tilde{\Theta}_d}{\sum \tilde{\Theta}_\infty} \tag{16}$$

Equation (16) is the final and fundamental equation which will be used to generate the resulting spillovers per frequency, and presented in spillover tables (and graphs) in section 4 to follow.

[14] A frequency band is defined as the amount of forecast error variance created on a convex set of frequencies. The quantity of variance is measured by integrating over the desired frequencies $\omega \in (a, b)$ in equation (13) to follow.

4. Empirical Results and Discussion

The fourth section of the paper is concerned with the representation of the results of all three of the models presented, namely: the GARCH model, the time-domain model and the frequency-domain model. Specifically, the results of both the asymmetric multivariate GARCH model (4.1) and the spillover measures of returns (4.2.1) and volatility (4.2.2) for both domain models. To assess the model stability over time, the results of the rolling window analysis are then subsequently presented in section 4.3.

4.1. Asymmetric Multivariate GARCH Model

Equations (2) and (4) are simultaneously estimated by the maximum log-likelihood approach. Selected coefficient estimates are presented in Table 6 to follow, with the asterisks indicating the significance levels of each value.[15] Table 6 also provides the Ljung-Box (LB) statistics and their p-values for tests on the residuals and their squares to measure the fit of the mean and volatility equations, respectively. For a properly specified model, the residuals of the fitted model should be white noise. This implies that there is no remaining serial correlation in the mean or volatility equation i.e. the model explains almost all variation and is therefore accurate. Formally, the LB test is used to test for randomness in the noise terms. This model verification test is also most common throughout the relevant GARCH literature (Mohammed and Tan, 2015; Kuttu, 2014; Bonga-Bonga and Hoveni, 2011; Worthington and Higgs, 2004). The LB statistics indicate that the GARCH model is a good fit for both the mean and volatility equations, with both having large p-values to establish a non-rejection of the null hypothesis of non-random errors at all significance levels. The model has been established as a good fit and its results may now be studied. As the A matrix associates returns with their one week lags, and all five diagonal coefficients A_{mm} are significant at at least the 5% level – intra-market return linkages are at play. This means that each market's previous returns are a good indication of their current week's returns, which is expected given how returns are calculated in this paper.

[15]($*$) indicates 10%, ($**$) indicates 5%, ($***$) indicates 1% level of significance in Table 6. Standard errors are not reported in Table 7 to save space.

Table 6: Summarised Results of the Estimated Asymmetric Multivariate BEKK-GARCH(1,1) Model

	South Africa	Nigeria	Egypt	Morocco	Tunisia
	(m = 1)	*(m = 2)*	*(m = 3)*	*(m = 4)*	*(m = 5)*
A_{m1}	0.0050**	0.0083*	0.0026	0.0015	0.0006
A_{m2}	0.0008*	0.0778**	0.0008	0.0003	-0.0005
A_{m3}	0.0026	0.0008	0.0260***	0.0008	0.0013
A_{m4}	0.0015	0.0003	0.0008	0.0053**	0.0010
A_{m5}	0.0006**	-0.0005	0.0013	0.0010**	0.0030***
B_{mm}	0.0027***	0.0028**	0.0036***	0.0008***	0.0023***
D_{m1}	0.9543**	0.0288	0.3592	0.0362	0.0245
D_{m2}	-0.0016	-0.8839***	0.0370	0.0110	0.0510
D_{m3}	-0.0915	0.0667	0.5676***	0.0911*	0.0081
D_{m4}	-0.0734	-0.0037	-0.2419*	0.8918***	-0.0362*
D_{m5}	-0.0910	0.0100	-0.2791**	0.0074**	0.9340***
E_{m1}	0.2406*	-0.0846*	-0.5000*	-0.1140	-0.0501**
E_{m2}	0.0256	0.4008	-0.0598*	-0.0271**	0.0200*
E_{m3}	0.0816	-0.0157**	0.3980	-0.0091*	0.0510
E_{m4}	0.1579	0.0188*	0.5000**	0.3732**	-0.0209*
E_{m5}	0.1906	0.0200*	0.4993	0.0283*	0.2771
LB-Q(10)	10.0325				
p-value	0.4376				
LBsq-Q(10)	29.0816				
p-value	0.8992				

The only significant bi-directional return spillover exists between South Africa and Nigeria. In addition, Egypt does not transmit nor receive significant weekly returns from the other markets (as only C_{33} is significant) but weekly Moroccan and South African returns are found to significantly spillover to the Tunisian equity market. In other words, the mean Tunisian return is influenced in future periods of one week by the present return shocks to Moroccan and South African equities, *ceteris paribus*. The constant matrix B does not shed any light on the transmission effect but the fact that all five of its elements are extremely significant indicates a noteworthy intercept in the return model. From the diagonal elements of matrix D it is clear that the African markets respond sharply to their own past return shocks and past volatility. The off-diagonal elements represent the volatility spillover and the Morocco-Egypt and Egypt-Tunisia pairs show cross-market volatility connectedness. Specifically, current week shocks to Morocco (Egypt) significantly influence average volatility in Egypt (Tunisia) in the following week, *ceteris paribus*. The off-diagonal of matrix E represents the volatility response of a market to other markets' negative shocks. Most the off-diagonal elements of E are significant, with only South African markets not really reacting to negative shocks from the other markets, indicating again the presence asymmetric volatility. Egypt is also only slightly reactive to these shocks but the remaining three African markets react strongly to shocks from other markets.

To summarise, the GARCH model estimates suggest that the African equity markets are quite closely linked in return and volatility but only reports this connectivity on a pairwise level instead of as a whole. In other words, certain country pairs are related which could lead the reader to believe that this increases connectiveness across the region. The spillover results in both section 4.2 and 4.3 to follow will confirm whether the supposed linkages are supported by the spillover analysis.

4.2. Spillovers

The Diebold-Yielmaz (2012) (time-domain) and Barunik-Khrehlik (2018) (frequency-domain) methods, as outlined in section 3.2, are applied to both market return and market volatility data to quantify the spillover effects within the African equity market context in this paper. First, for the time-domain analysis, the five variable VAR model is fitted to each series according to equation (5) and the lag length (p) is selected according to both the Akaike Information Crietria (AIC) and the Bayesian Information Criteria (BIC).[16] For the frequency-domain analysis and robustness purposes, four frequency bands were selected to represent the different intervals. By way of example, the selected frequencies are: short-term (1 to 2 weeks), short to medium-term (2 to 8 weeks), medium to long-term (8 to 24 weeks) and long-term (more than 24 weeks).

The spillover results are organised into three categories: overall spillover, net spillover and net pairwise spillover, where both the Diebold-Yilmaz (2012) (DY) and Barunik-Khrehlik (2018) (BK) method results are displayed for each of the aforementioned categories. In the overall spillover tables "From" represents where the spillover originated, "To" represents the receiver of the spillover, "Abs" represents the absolute value of the spillover and "Wtn" represents spillovers to (from) one country from (to) the sampled countries. The spillover percentages are reported as averages.

[16]The optimal p lag was calculated to be 1 for both for returns and volatility when using the BIC. Under the AIC the optimal lag was 2 and 12 for returns and volatility, respectively. AIC was selected, with similar reasoning to to Matsuki *et al.* (2014), to avoid introducing a possible bias in the estimates because of the omitted variable problem. As a robustness check, the VAR regression was re-estimated with both options, but the qualitative results remained unchanged.

4.2.1. Return

Table 7: Overall return spillover results

DY(2012)	SA	Nigeria	Egypt	Morocco	Tunisia	From
SA	86.27	0.39	8.66	3.75	0.92	2.75
Nigeria	2.66	92.36	2.22	2.46	0.31	1.53
Egypt	9.96	1.29	85.23	2.72	0.80	2.95
Morocco	4.41	0.75	4.14	90.17	0.54	1.97
Tunisia	0.63	0.45	0.97	0.53	97.42	0.52
To	3.53	0.58	3.20	1.89	0.51	**9.71**

Table 8: Overall return spillover results in the short-term

BK(2018)	SA	Nigeria	Egypt	Morocco	Tunisia	From (Abs)	From (Wth)
SA	48.36	0.34	5.64	2.86	0.87	1.94	3.96
Nigeria	0.27	44.25	0.13	0.22	0.19	0.16	0.33
Egypt	2.46	0.83	44.10	0.93	0.35	0.91	1.86
Morocco	1.52	0.38	1.96	44.78	0.38	0.85	1.72
Tunisia	0.18	0.11	0.37	0.21	43.60	0.17	0.36
To (Abs)	0.89	0.33	1.62	0.84	0.36	**4.04**	
To (Wth)	1.81	0.67	3.30	1.72	0.73		8.23

Table 9: Overall return spillover results in the short to medium-term

BK(2018)	SA	Nigeria	Egypt	Morocco	Tunisia	From (Abs)	From (Wth)
SA	27.97	0.02	2.17	0.54	0.03	0.55	1.59
Nigeria	1.37	34.44	1.12	1.28	0.12	0.78	2.22
Egypt	4.41	0.19	28.26	0.90	0.29	1.16	3.32
Morocco	1.41	0.16	1.02	31.83	0.10	0.54	1.54
Tunisia	0.33	0.17	0.36	0.24	35.68	0.22	0.63
To (Abs)	1.50	0.11	0.93	0.59	0.11	**3.24**	
To (Wth)	4.31	0.31	2.68	1.70	0.31		9.30

Table 10: Overall return spillover results in the medium to long-term

BK(2018)	SA	Nigeria	Egypt	Morocco	Tunisia	From (Abs)	From (Wth)
SA	6.09	0.02	0.51	0.21	0.01	0.15	1.54
Nigeria	0.60	8.33	0.57	0.57	0.01	0.35	3.60
Egypt	1.82	0.16	7.76	0.52	0.09	0.52	5.35
Morocco	0.87	0.12	0.68	8.21	0.03	0.34	3.50
Tunisia	0.08	0.10	0.14	0.05	10.95	0.07	0.77
To (Abs)	0.67	0.08	0.38	0.27	0.03	**1.43**	
To (Wth)	6.95	0.82	3.92	2.77	0.29		14.76

Table 11: Overall return spillover results in the long-term

BK(2018)	SA	Nigeria	Egypt	Morocco	Tunisia	From (Abs)	From (Wth)
SA	3.86	0.01	0.34	0.14	0.01	0.10	1.58
Nigeria	0.42	5.33	0.40	0.39	0.00	0.24	3.80
Egypt	1.26	0.12	5.11	0.37	0.06	0.36	5.70
Morocco	0.62	0.09	0.48	5.35	0.03	0.24	3.82
Tunisia	0.05	0.07	0.09	0.03	7.18	0.05	0.76
To (Abs)	0.47	0.06	0.26	0.19	0.02	**1.00**	
To (Wth)	7.37	0.91	4.13	2.95	0.31		15.67

Table 7 illustrates the overall connectedness of the returns of the five markets under the time-domain approach, calculated by equation (10). The results indicate that equities in the African markets only transmit an average of 9.71% of their returns within the region. These spillovers may seem low and could suggest that the top African equity markets are not very connected at all when returns are concerned, but they are in line and even slightly higher than results found in the relevant research. Matsuki *et al.* (2014) find a 5% connectedness of seven African markets across a variety of asset classes. Egypt contributed the most to the region at 2.95% of returns transmitted across the period. This is interesting since Egypt seemed quite disconnected from the rest of the sampled countries during the GARCH analysis. In contrast, Tunisia contributed 0.52% to overall return spillover, indicating its stark lack of power within the selected market space. But, overall intra-market return spillovers exceed 85% over the entire sample (diagonals of Table 8). This means that at least 85% of returns in the current week come from the returns of the previous week, in the same country, which is supported by the GARCH analysis.

Table 12: Net return spillover results

DY(2012)	South Africa	Nigeria	Egypt	Morocco	Tunisia
	-0.7867	**0.9514**	-0.2427	0.0733	0.0047

Table 13: Net return spillover results in the short-term

BK(2018)	South Africa	Nigeria	Egypt	Morocco	Tunisia
	-1.0546	0.1695	0.7045	-0.0012	0.1817

Table 14: Net return spillover results in the short to medium-term

BK(2018)	South Africa	Nigeria	Egypt	Morocco	Tunisia
	0.9486	-0.6671	-0.2236	0.0541	-0.1119

Table 15: Net return spillover results in the medium to long-term

BK(2018)	South Africa	Nigeria	Egypt	Morocco	Tunisia
	0.5248	-0.2696	-0.1386	-0.0705	-0.0460

Table 16: Net return spillover results in the long-term

BK(2018)	South Africa	Nigeria	Egypt	Morocco	Tunisia
	0.3678	-0.1841	-0.0995	-0.0556	-0.0284

Table 17: Net pairwise spillover results

DY (2012)	SA-Nig	SA-Egy	SA-Mor	SA-Tun	Nig-Egy	Nig-Mor	Nig-Tun	Egy-Mor	Egy-Tun	Mor-Tun
	-0.45	-0.26	-0.13	0.06	0.18	0.34	-0.02	-0.28	-0.03	**0.01**

Table 18: Net return pairwise spillover results in the short-term

BK (2018)	SA-Nig	SA-Egy	SA-Mor	SA-Tun	Nig-Egy	Nig-Mor	Nig-Tun	Egy-Mor	Egy-Tun	Mor-Tun
	0.01	0.63	0.27	0.14	-0.14	-0.03	0.01	-0.20	-0.01	0.03

Table 19: Net return pairwise spillover results in the short to medium-term

BK (2018)	SA-Nig	SA-Egy	SA-Mor	SA-Tun	Nig-Egy	Nig-Mor	Nig-Tun	Egy-Mor	Egy-Tun	Mor-Tun
	-0.27	-0.45	-0.17	-0.06	0.19	0.22	-0.01	-0.03	-0.02	-0.01

Table 20: Net return pairwise spillover results in the medium to long-term

BK (2018)	SA-Nig	SA-Egy	SA-Mor	SA-Tun	Nig-Egy	Nig-Mor	Nig-Tun	Egy-Mor	Egy-Tun	Mor-Tun
	-0.12	-0.26	-0.13	-0.01	0.08	0.09	-0.02	-0.03	-0.01	-0.01

Table 21: Net return pairwise spillover results in the long-term

BK (2018)	SA-Nig	SA-Egy	SA-Mor	SA-Tun	Nig-Egy	Nig-Mor	Nig-Tun	Egy-Mor	Egy-Tun	Mor-Tun
	-0.08	-0.18	-0.09	-0.01	0.06	0.06	-0.01	-0.02	-0.01	-0.00

When comparing the overall return spillovers to the decomposed effects at different frequencies measured by employing the Barunik and Khrehlik (2018) procedure in Table 8 to 11, there are clear magnitude differences between the spillovers at certain periods. Evidently, the equity market returns are more connected at higher frequencies i.e. the short-run. Total spillover from the lowest frequency is 4.04% of the total connectedness which decreases to 1% at the highest frequency i.e. the long-run. This means that total connectedness of the African markets is higher in the short-run than in the long-run, which supports the findings of Cunado *et al.* (2018) suggesting that "portfolio diversification opportunities are lower in the short-run". But unlike Cunado *et al.* (2018), the highest country contributor across frequencies is variable. Therefore, from an investment point of view, investors are already diversifying by holding different African equities but should hold their portfolios for more than 24 weeks to optimise their diversification gains.

It is clear from Table 12 to 16 that the largest African equity market by market capitalisation is a net transmitter of returns (transmits more than it receives) (-0.79%) which seems expected given its size in the region, but when considering the decomposed returns it is clear that South Africa transmits the largest returns only in the short-term (1.1%) before becoming a receiver in the medium-term. The same is true for Egypt which is also a net transmitter and transmits most of its returns in the short-term too. The return findings of this section do also support Matsuki *et al.* (2014) who find that South Africa and Egypt are net transmitters of return and that Morocco and Tunisia are net receivers of this return (Table 12). Nigeria is also a net receiver of return, but could not be compared to the results of Matsuki *et al.* (2014) as this study did not include Nigeria. In terms of the DY (2012) pairwise relationships reported in Table 17, South Africa-Nigeria have the largest pairwise contribution (although negative), and also both return spillover coefficients on the off-diagonal of matrix A in the GARCH model are significant signifying a mutual market dependency. The reader can recall that South Africa and Nigeria were the only significant bi-directional return spillover too. The Morocco-Tunisia pair is the lowest net contributor of return, although in the GARCH model the inter-market return coefficient on the off-diagonal of matrix A is only signficiant for the unidirectional Morocco to Tunisia spillover.

4.2.2. Volatility

In contrast to the return spillover tables, the African equity markets are much more connected in terms of volatility than in terms of returns. Table 22 to follow, displays that as much as 19.9% of volatility in the market, on average, is spilled over from within the five variable system. There is not much literature on volatility connectedness in Africa specifically, but Salisu *et al.* (2018) calculate a 22.7% volatility spillover index for six major global currencies.

Table 22: Overall volatility spillover results

DY(2012)	SA	Nigeria	Egypt	Morocco	Tunisia	From
SA	71.42	2.32	12.46	11.29	2.52	5.72
Nigeria	7.05	85.07	3.77	2.74	1.36	2.99
Egypt	5.95	1.33	84.07	5.13	3.52	3.19
Morocco	21.67	1.77	11.02	63.96	1.57	7.21
Tunisia	0.99	0.53	1.57	0.98	95.93	0.81
To	7.13	1.19	5.76	4.03	1.79	**19.91**

Table 23: Overall volatility spillover results in the short-term

BK(2018)	SA	Nigeria	Egypt	Morocco	Tunisia	From (Abs)	From (Wth)
SA	24.50	0.46	3.29	3.30	0.52	1.51	3.97
Nigeria	1.02	33.25	1.26	0.89	0.48	0.73	1.92
Egypt	1.79	0.65	30.60	1.74	1.41	1.12	2.93
Morocco	4.20	0.78	5.15	24.98	0.46	2.12	5.56
Tunisia	0.55	0.34	0.73	0.34	47.73	0.39	1.03
To (Abs)	1.51	0.45	2.09	1.25	0.57	**5.87**	
To (Wth)	3.97	1.17	5.48	3.29	1.51		15.41

Table 24: Overall volatility spillover results in the short to medium-term

BK(2018)	SA	Nigeria	Egypt	Morocco	Tunisia	From (Abs)	From (Wth)
SA	19.21	0.81	2.49	2.30	0.59	1.24	3.83
Nigeria	1.38	30.38	0.73	0.95	0.40	0.69	2.13
Egypt	1.05	0.40	34.76	0.65	1.24	0.67	2.06
Morocco	6.10	0.68	2.39	22.16	0.32	1.90	5.85
Tunisia	0.33	0.15	0.66	0.33	31.47	0.29	0.91
To (Abs)	1.77	0.41	1.25	0.85	0.51	**4.79**	
To (Wth)	5.47	1.26	3.87	2.61	1.58		14.79

Table 25: Overall volatility spillover results in the medium to long-term

BK(2018)	SA	Nigeria	Egypt	Morocco	Tunisia	From (Abs)	From (Wth)
SA	6.58	0.30	2.08	1.27	0.43	0.82	8.98
Nigeria	0.35	7.29	0.29	0.13	0.02	0.16	1.75
Egypt	0.81	0.06	9.88	1.14	0.40	0.48	5.30
Morocco	2.13	0.17	1.07	4.88	0.20	0.71	7.86
Tunisia	0.07	0.00	0.04	0.08	5.76	0.04	0.43
To (Abs)	0.67	0.11	0.70	0.52	0.21	**2.21**	
To (Wth)	7.39	1.19	7.67	5.75	2.31		24.32

Table 26: Overall volatility spillover results in the long-term

BK(2018)	SA	Nigeria	Egypt	Morocco	Tunisia	From (Abs)	From (Wth)
SA	21.13	0.74	4.60	4.42	0.98	2.15	10.51
Nigeria	4.30	14.14	1.49	0.77	0.45	1.40	6.87
Egypt	2.31	0.22	8.83	1.60	0.47	0.92	4.50
Morocco	9.24	0.13	2.41	11.94	0.60	2.48	12.12
Tunisia	0.05	0.03	0.14	0.23	10.96	0.09	0.44
To (Abs)	3.18	0.23	1.73	1.40	0.50	**7.04**	
To (Wth)	15.56	1.11	8.45	6.87	2.44		34.44

These results are supported by most of the existing literature around global equity market spillovers, finding that they are "usually higher and more abrupt than return spillovers" (Diebold and Yilmaz, 2009). The Moroccan equity market drove volatility connectedness the most at 7.2% with Tunisia having almost no inter-market contribution, significantly lower than the others as with returns, at 0.81% contribution to the overall volatility transmission, seen in Table 22. This should lead the reader to believe that perhaps Tunisia is too small a market (only US$ 9 billion in market capitalisation) to have much influence or it could be due to the nature of the TUNINDEX being very illiquid and the fact that the majority of companies in the index belong to a similar sector (ASEA, 2018).

Table 27: Net volatility spillover results

Total DY(2012)	South Africa	Nigeria	Egypt	Morocco	Tunisia
	-1.4183	1.2961	-1.7907	**3.1802**	0.9796

Table 28: Net volatility spillover results in the short-term

BK(2018)	South Africa	Nigeria	Egypt	Morocco	Tunisia
	-0.0006	-0.2866	0.9685	-0.8643	0.1830

Table 29: Net volatility spillover results in the short to medium-term

BK(2018)	South Africa	Nigeria	Egypt	Morocco	Tunisia
	0.5310	-0.2825	0.5850	1.0497	0.2162

Table 30: Net volatility spillover results in the medium to long-term

BK(2018)	South Africa	Nigeria	Egypt	Morocco	Tunisia
	0.1447	-0.0501	0.2156	-0.1921	0.1713

Table 31: Net volatility spillover results in the long-term

BK(2018)	South Africa	Nigeria	Egypt	Morocco	Tunisia
	-1.0327	-1.1769	0.8091	1.0740	0.4091

Table 32: Net pairwise volatility spillover results

DY (2012)	SA-Nig	SA-Egy	SA-Mor	SA-Tun	Nig-Egy	Nig-Mor	Nig-Tun	Egy-Mor	Egy-Tun	Mor-Tun
	-0.95	**-1.30**	-1.08	0.31	0.49	0.20	0.17	**2.18**	0.39	0.12

Table 33: Net pairwise volatility spillover results in the short-term

BK (2018)	SA-Nig	SA-Egy	SA-Mor	SA-Tun	Nig-Egy	Nig-Mor	Nig-Tun	Egy-Mor	Egy-Tun	Mor-Tun
	-0.11	0.30	-0.18	-0.01	0.12	0.02	0.03	-0.68	0.14	0.02

Table 34: Net pairwise volatility spillover results in the short to medium-term

BK (2018)	SA-Nig	SA-Egy	SA-Mor	SA-Tun	Nig-Egy	Nig-Mor	Nig-Tun	Egy-Mor	Egy-Tun	Mor-Tun
	-0.11	0.29	-0.78	0.05	0.07	0.05	0.05	-0.35	0.12	-0.00

Table 35: Net pairwise volatility spillover results in the medium to long-term

BK (2018)	SA-Nig	SA-Egy	SA-Mor	SA-Tun	Nig-Egy	Nig-Mor	Nig-Tun	Egy-Mor	Egy-Tun	Mor-Tun
	-0.01	0.26	-0.17	0.07	0.05	-0.01	0.00	0.01	0.07	0.02

Table 36: Net pairwise volatility spillover results in the long-term

BK (2018)	SA-Nig	SA-Egy	SA-Mor	SA-Tun	Nig-Egy	Nig-Mor	Nig-Tun	Egy-Mor	Egy-Tun	Mor-Tun
	-0.71	0.46	-0.96	0.18	0.25	0.12	0.08	-0.16	0.07	0.07

Moving on to Tables 22 to 25, the BK (2018) methodology produces results which show, once again, that the degree of connectedness among African equity markets differs at different frequencies. Specifically, equity volatility transmission is the highest for over 24 weeks post-origination at 7% (long-term), compared to 5.9% for 1 to 2 weeks (short-term). The long-term significance of volatility is evident, mostly driven by South Africa and Morocco at over 10% each (Table 25). In the medium-term, between 8 and 24 weeks, is when the markets are the least connected in terms of volatility spillovers (2.2% in Table 25). Toyoshima and Hamori (2018) follow a similar procedure to this paper but instead focus on the connectedness of crude oil markets. This paper supports the findings of Toyoshima and Hamori (2018) who find that that the total connectedness among markets for returns is higher in the short-term than in the long-term and that for volatility this value is higher in the short-term than in the long-term. Therefore, for investors to mitigate risk by avoiding the effects of a negative shock, they should consider that the African markets will have the least amount of correlated volatility transmission effects present in the medium-term, specifically 8 to 24 weeks.

Table 27 shows that Morocco is the largest net receiver of volatility and South Africa is once again the largest transmitter. From the GARCH approach, only the South African markets were not as reactive to negative shocks from the other markets, which is confimed by Table 31 which shows that South Africa transmits most of its volatility in the long-term (-1.0327%) but is a net receiver in the short-term. It is also noteworthy that the South Africa-Egypt pair yields the largest net pairwise volatility transmission (contribution) at 1.3% in Table 32 although neither directional coefficient is significant in the GARCH framework. There is also a strong pairwise transmission effect between Egypt and Morocco at 3.18% which is also significant in the GARCH model as a bidirectional relationship from the significance of the off-diagonals for both countries in matrix D.

4.3. Rolling window analysis

In order to assess the nature of spillover variation over time, the rolling window approach to forecasting is employed. This approach aims to "backtest" the time and frequency-domain models on historical data to evaluate stability and predictive accuracy. It involves calculating the spillovers for a subsample of the data which is then rolled forward while keeping the size of the subsample constant for each period. This is a useful method of studying the time-frequency dynamics of the equity series' to ascertain the dynamic interconnectivity of African markets. If the rolling window analysis shows that market connectedness is dependent on time, suggests a possible link between noteworthy events and equity market movements.

The forecast horizon (H) refers to the number of periods ahead the rolling window should be computed to assess the spillover nature over time. According to Barunik and Khrehlik (2018) this number should be high enough so that it will not change with additional periods. Following this logic, a 100-week (2 year) forecast horizon was used with a 200-week (3 years and 10 months) rolling window. To illustrate the mechanics of this process with an example: the spillover in 2006 week 1 is calculated by taking into account the estimated spillover from 2002 week 40 to 2005 week 52.[17]

Figure 11. Overall Return Spillover

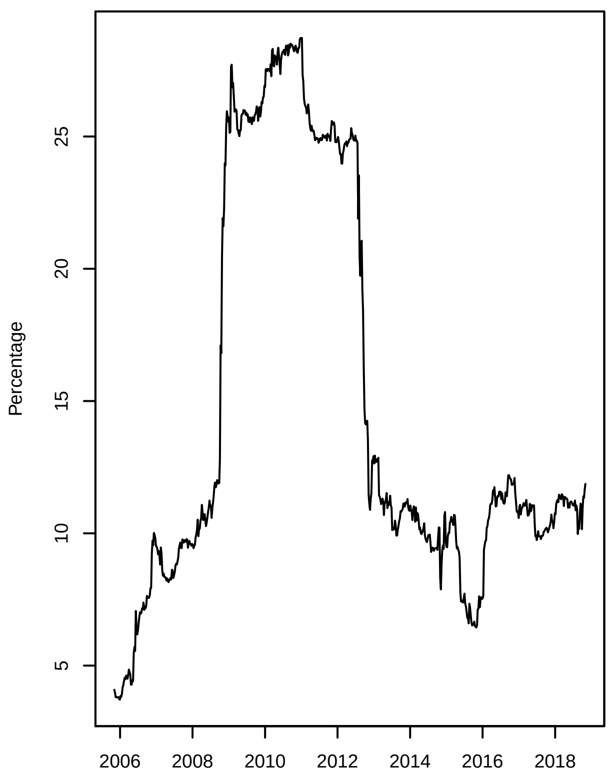
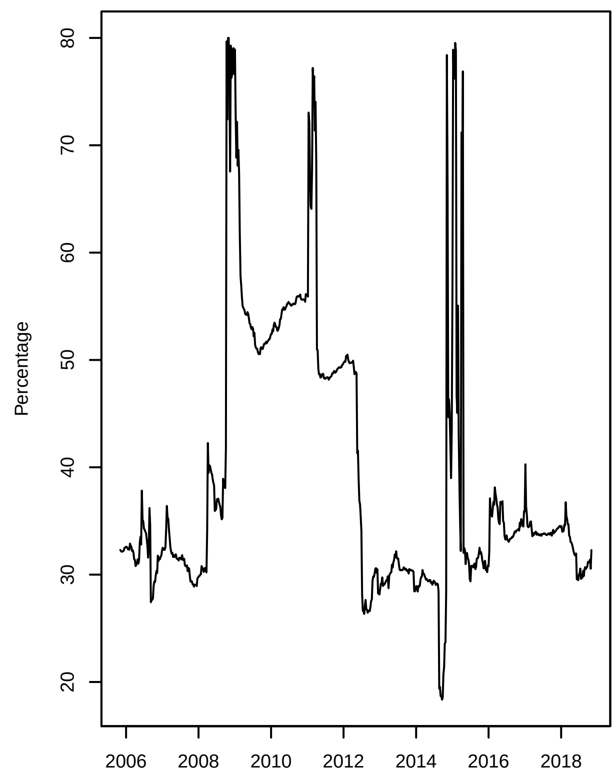


Figure 12. Overall Volatility Spillover



[17] The frequency-domain rolling window Figures 13 to 20 are presented using the same axes for returns and the same axes for volatility for ease of comparison.

Figure 13.Short−term Return Spillover

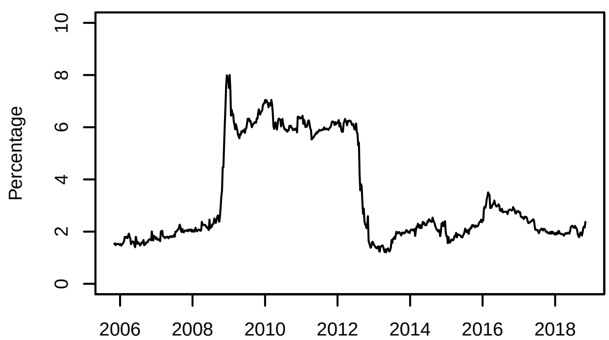


Figure 14.Short−term Volatility Spillover

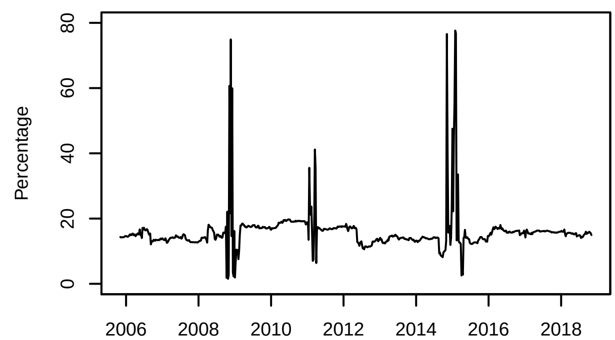


Figure 15.Short to medium−term Return Spillover

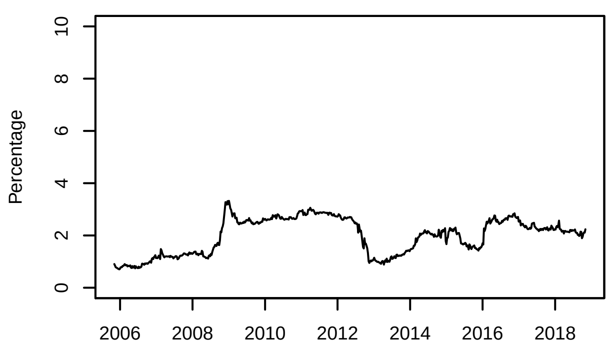


Figure 16.Short to medium−term Volatility Spillove

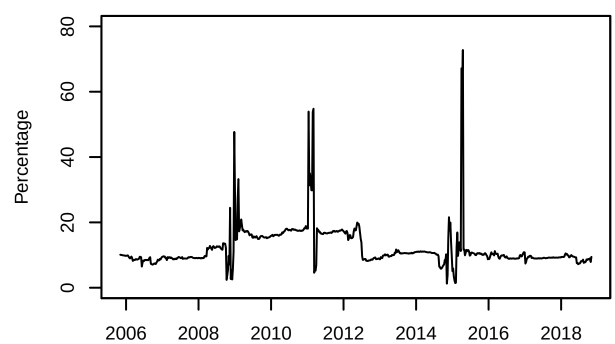


Figure 17.Medium to long−term Return Spillover

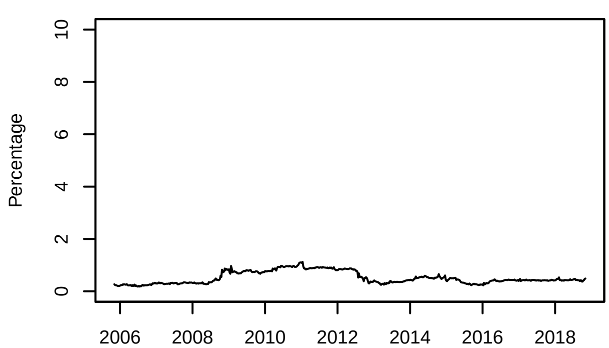


Figure 18.Medium to long−term Volatility Spillover

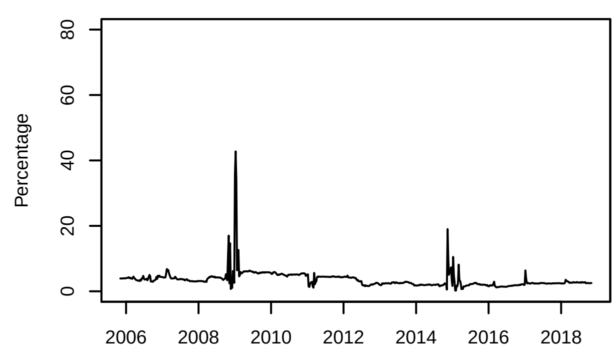


Figure 19.Long−term Return Spillover

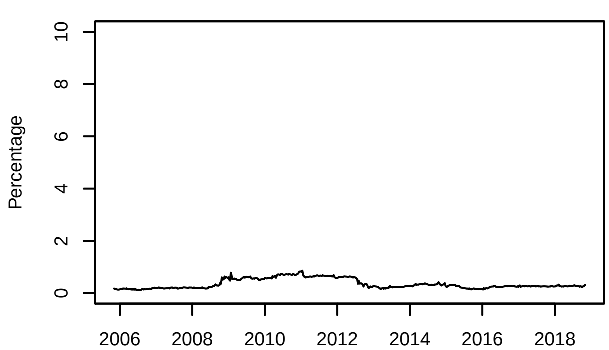
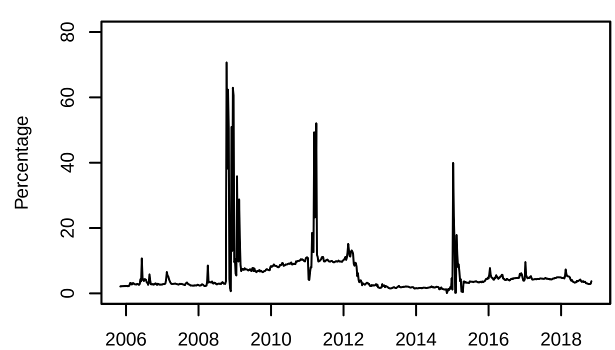


Figure 20.Long−term Volatility Spillover



The full sample spillover tables presented in section 4.2 provide a useful summary of average behaviour but these methods may miss potentially important movements in spillovers over time. Therefore, the rolling window analysis is deployed to capture the effect of significant events or crisis episodes within the sample. Noteworthy events of turmoil during the sample include the GFC of 2008 and 2009, the Jasmine revolution in Tunisia in late 2010, the largest anti-goverment protests in Egypt in 2011 and Nenegate in South Africa in 2015.[18] Figure 11 and 12 represent the time plots of overall spillovers using the DY (2012) method. These two plots juxtapose the erratic behaviour of volatility spillovers against the return spillovers which despite during the GFC of 2008 and 2009, have only seen small peaks and troughs but followed a general upward trend over time. The return spillovers hover around 10% but have gradually increased and continued doing so since the early 2000s where the African markets were hardly connected at less than 5% spilled over within the region. This result captures the inklings from the literature: that the African markets have become even more integrated with investment within Africa trending upward (Bonga-Bonga and Hoveni, 2011). Additionally, one can notice the sharp spikes in both return and volatility connectedness in 2008 and 2009, in 2010, 2011 and in 2015. Volatility is much more responsive to the shocks with effects of a crisis noticed soon after.

From the previous frequency-domain analysis it is evident that the degree of market connectedness is affected by the frequency – reinforced by the frequency graphs in Figures 13 to 20 – as the decomposed return and volatility charts do behave quite differently at different measured frequencies, but more so for return. Specifically, it is evident that the return spillovers are predominantly driven by the short-run but dissipate in the longer-term. The opposite is true for volatility. This paper also provides evidence for two points mentioned in Mastuki *et al.* (2014). First, that Tunisia became a net transmitter in the course of 2010 prior to the Jasmine revolution at the end of the year and second, that the net return spillovers of Egypt almost simultaneously jumped. Therefore, there is evidence that a crisis may switch a market from a receiver to a transmitter of net spillover and vice versa.[19]

In summary, during periods of crisis the African equity markets rely more heavily on one another evident in the rolling window analysis, but this is multiplied for volatility. Put simply, volatility is a much greater indicator of a crisis than returns. Price movements in one market spill over rapidly and this lasts for quite some time until investor sentiment improves. Arguably one of the most interesting findings of this paper is that of market volatility connectedness being substantially higher than return connectedness in Africa. Surely the explanation lies in the

[18]The Jasmine revolution was an uprising which led to the ousting of former president Zine al-Abidine Ben Ali which inspired similar Egyptian protests in the following year. This led to immense social disorder and uncertainty in Egypt that rippled through other African regions (Brittanica, 2012). “Nenegate” refers to the financial turmoil caused by the axing of then South African finance minister Nhlanhla Nene, which wiped half a trillion rand off the value of South African stocks and bonds (Silke, 2016).

[19]See the supplementary results in the Appendix for the country specific spillover graphs.

difference between the fundamental calculation of returns and volatility. One explanation could be that since volatility is modelled as the square of returns there is no signage bias as there is with returns. But it is clear that although the African markets are quite connected, these linkages have been increasing over time but not at the same rate as the developed markets which speaks to the existence of strong country-specific effects. In general, most of the GARCH results are confirmed by the spillover analysis.

5. Conclusion

This main aim of this paper is to determine the nature and degree of interdependence within the largest and oldest African equity markets between the period of 11 January 2002 and 2 November 2018. The five sample markets are South Africa, Egypt, Morocco, Nigeria and Tunisia. The objective is achieved by employing a GARCH and spillover analysis to measure the behaviour of return and volatility between markets, in crises and over time. This paper makes four key contributions. First, the African equity markets' total return connectedness index is relatively moderate at 9.7%, however, the total volatility connectedness index is much higher at 19.9%, which is also larger than many other findings in the literature such as Matsuki *et al.* (2014). Second, South Africa and Egypt are usually the net transmitters of both return and volatility spillovers, while Morocco, Nigeria and Tunisia are usually the net receivers of these spillovers. South Africa contributed most towards the total volatility in the system and spillovers do flow from more to less developed markets in the case of Tunisia, supporting Salisu *et al.* (2018). Regional spillovers within Africa are smaller than global ones, as found in Matsuki *et al.* (2014). This means that the African markets are insulated from global shocks, even though they are net receivers. Third, both return and volatility interconnectivity has increased over time. There are also a number of spikes that occurred during periods of turmoil, as these measures are particularly high during the global financial crisis of 2008 and 2009, the Jasmine revolution in Tunisia in 2010, the anti-government protests in Egypt in 2011 and during Nenegate in South Africa in 2015. Lastly, to consider the robustness of these results, various different frequency windows have been used, where it is noted that although the central tenant of the above findings are present across all frequency windows, the exact measure for the degree of African equity market connectedness is contingent on the frequency under consideration. The results are robust to the VAR lag structure, forecast horizon and rolling window width. It is undeniable how the African markets have become more connected and how this connection is only going to strengthen over time with further globalisation and regional integration. The importance of investing is clear, but this reseach adds to the argument that where, when and for how long one invests is of the utmost importance.

6. Improvements for Future Research

Some very interesting results have been established, which add to the rich literature on financial market modelling and tools for the international investor. It would be even more interesting to extend this study to extract specific *causation* from any existing market correlation and connectivity, for example including a causality-in-mean or causality-in-variance spillover test. Secondly, some of the results are potentially being obscured by the interconnectedness of the South African and Nigerian markets to other economies outside of Africa. An extention of the modelling used which accounts for spillover effects in a sample such as this, where volatility in equity markets is generally considered to be quite high, is a thought-provoking experiment. It could also be captivating to do a similar study involving the foreign exchange markets or even multiple asset classes of each market for comparative purposes. Finally, focusing on researching the innate reasoning behind the differing results for return and volatility spillovers could be a valuable extention to this study.

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8. Appendix

8.1. Unit Root Testing

Table 37: Results of the Augmented Dickey Fuller Test

	Prices				
	SA	Nigeria	Egypt	Morocco	Tunisia
Test stat	-2.4921856	-2.4290042	-2.2181933	-1.5634195	-2.6424560
p-value	0.3699691	0.3967136	0.4859494	0.7631135	0.3063601

Table 38: Results of the Augmented Dickey Fuller test after transformation

	Returns				
	SA	Nigeria	Egypt	Morocco	Tunisia
Test stat	-9.105662	-7.585212	-8.379379	-7.585212	-8.176741
p-value	0.010000	0.010000	0.010000	0.010000	0.010000

8.2. Supplementary Results

Figure 20. South African Equity Prices

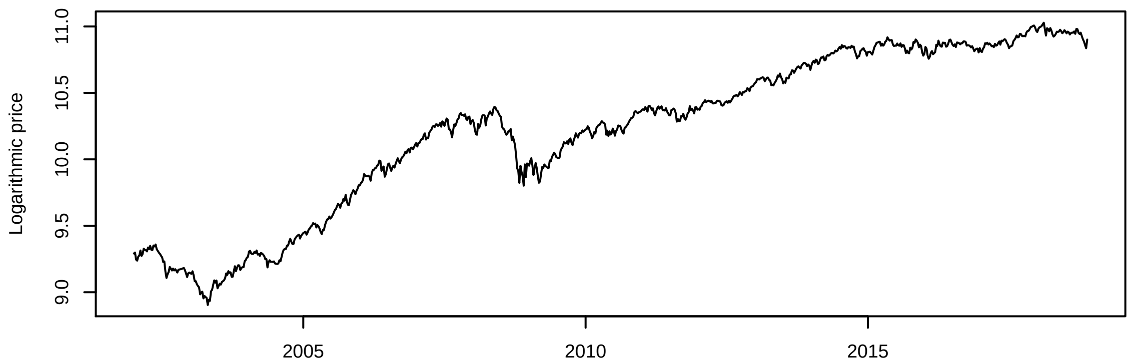


Figure 21. Nigerian Equity Prices

Figure 22. Egyptian Equity Prices

Figure 23. Moroccan Equity Prices

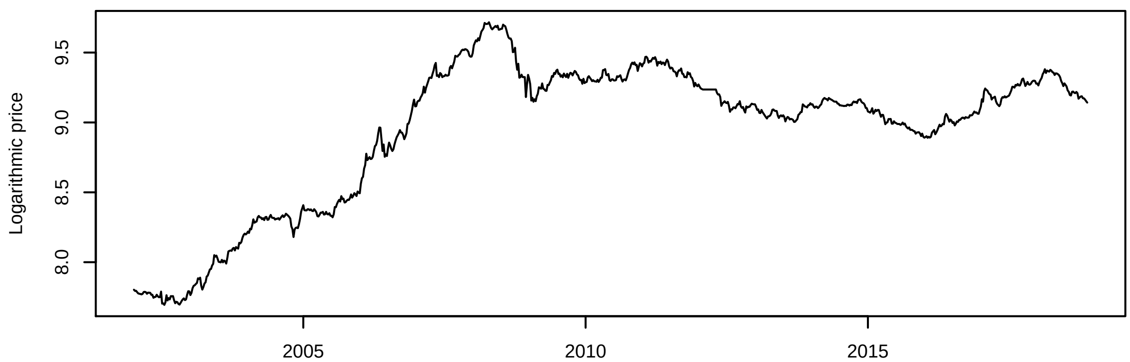
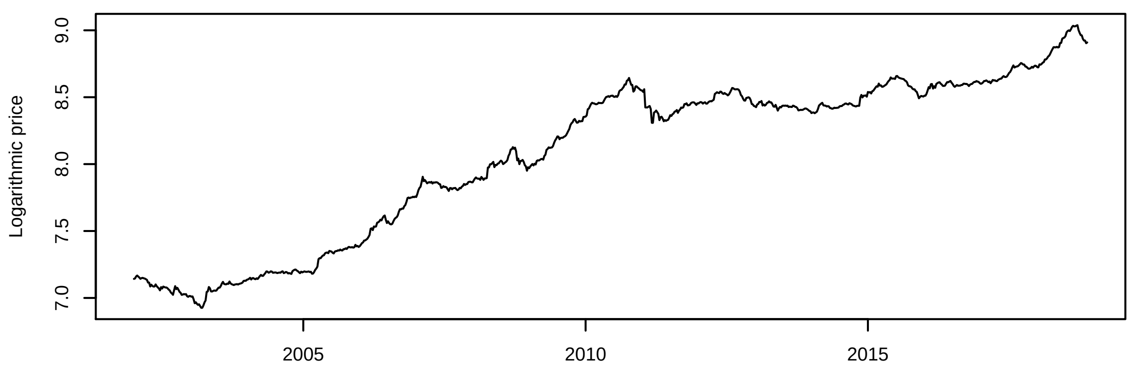


Figure 24. Tunisian Equity Prices



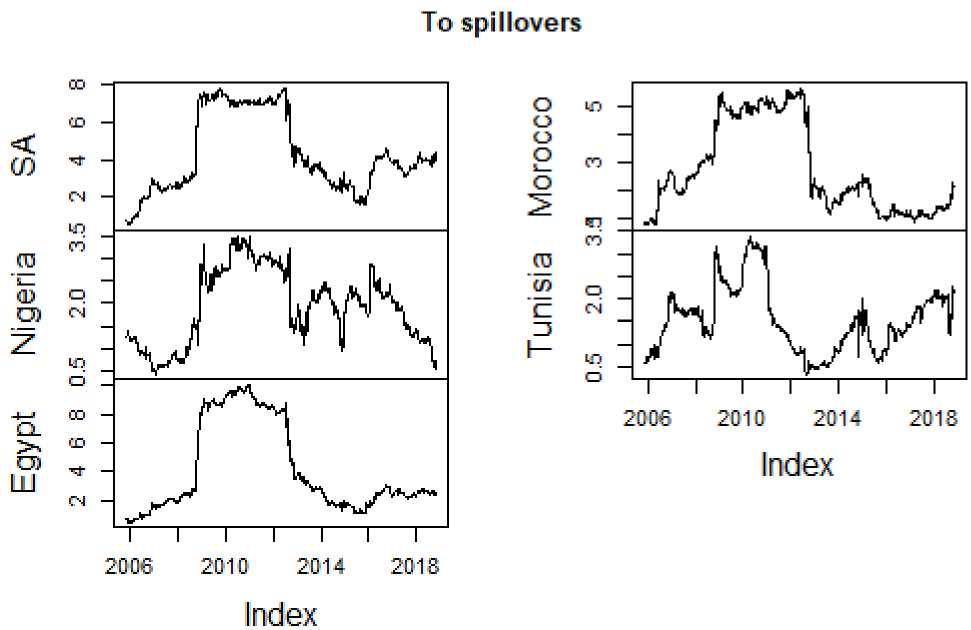


Figure 1: DY Return “To” Spillovers

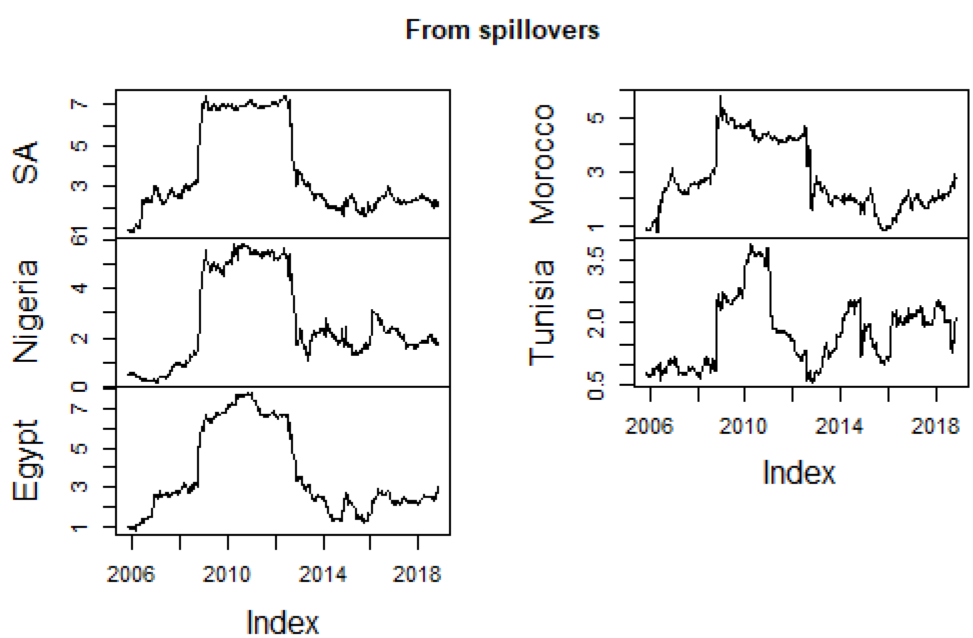


Figure 2: DY Return “From” Spillovers

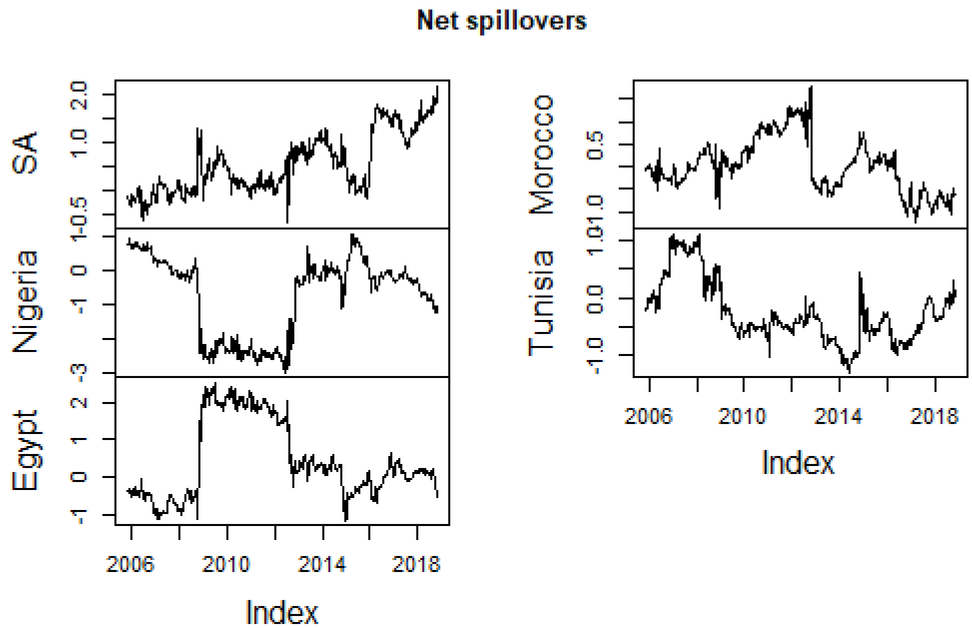


Figure 3: DY Return "Net" Spillovers

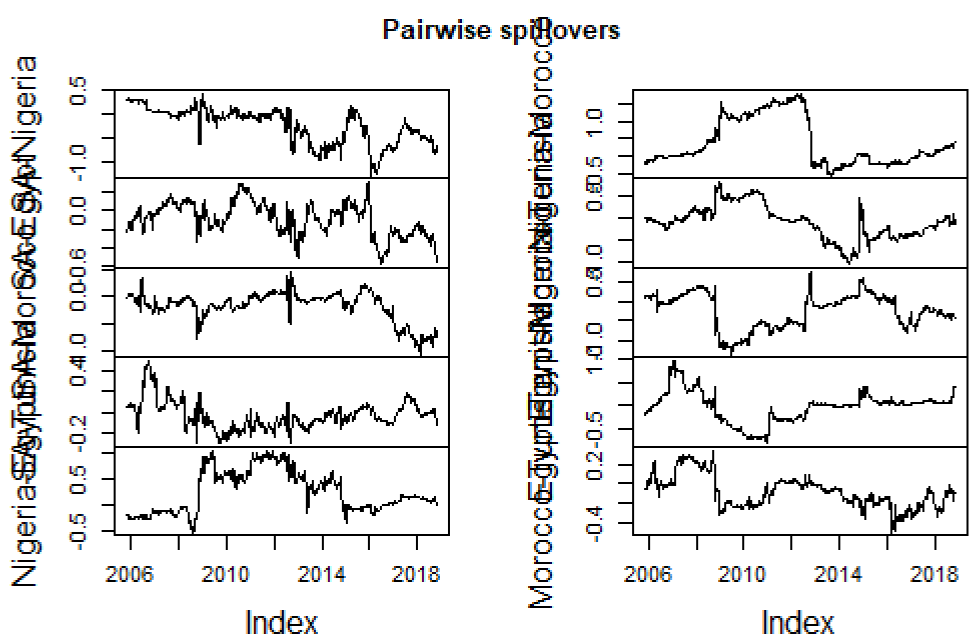


Figure 4: DY Return "Pairwise" Spillovers

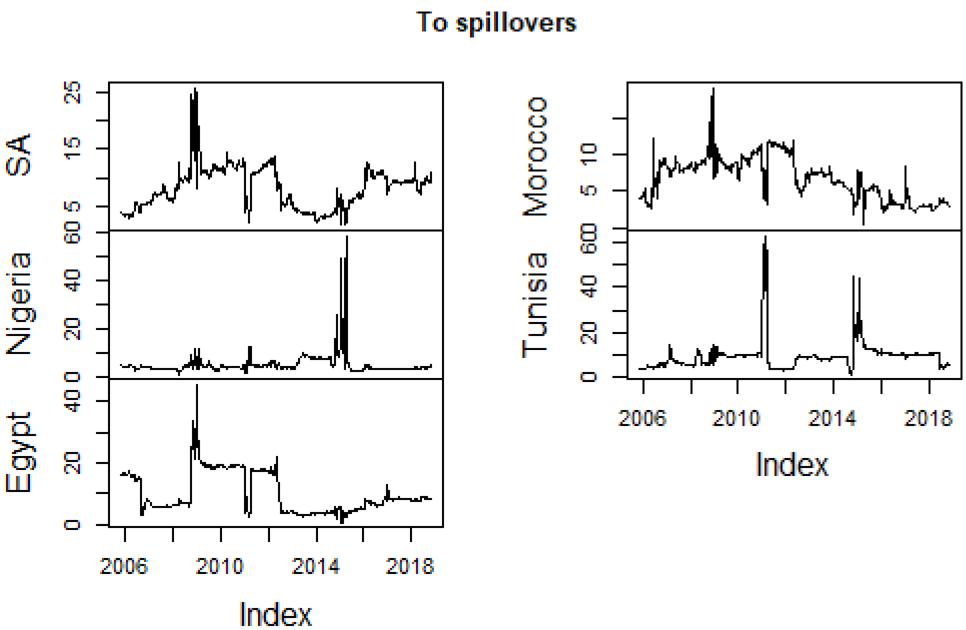


Figure 5: DY Volatility "To" Spillovers

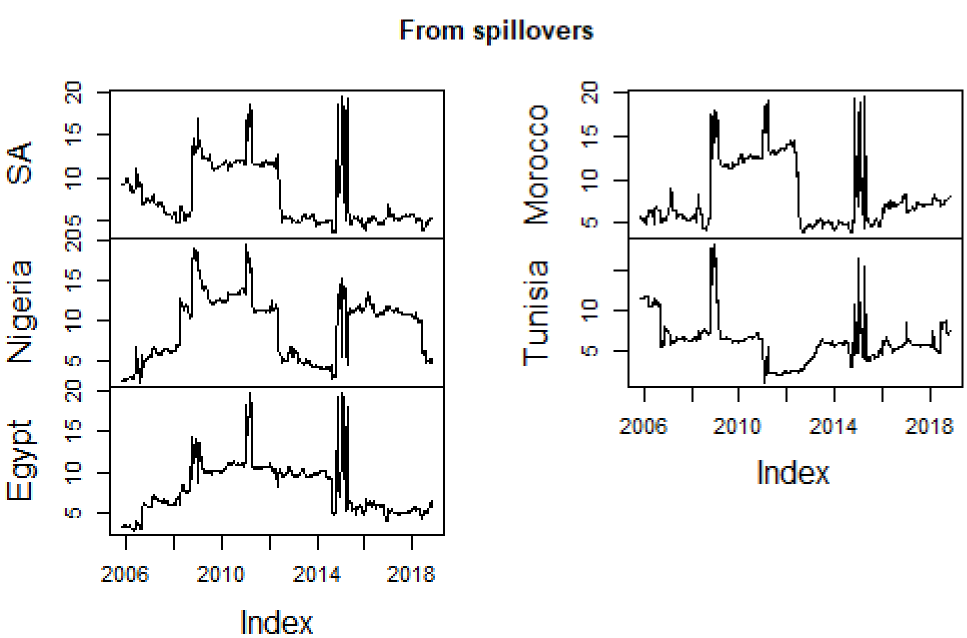


Figure 6: DY Volatility "From" Spillovers

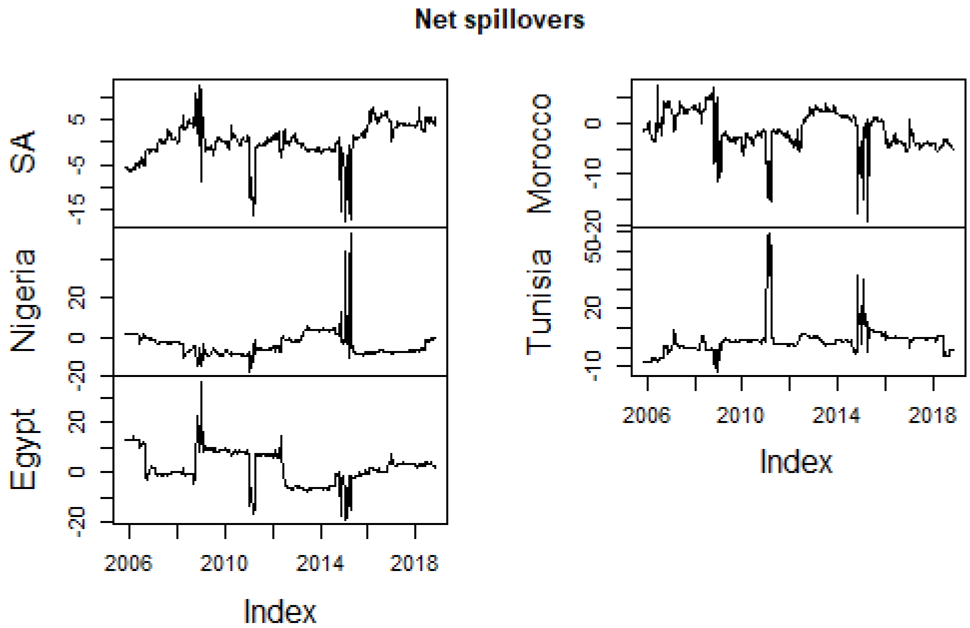


Figure 7: DY Volatility “Net” Spillovers

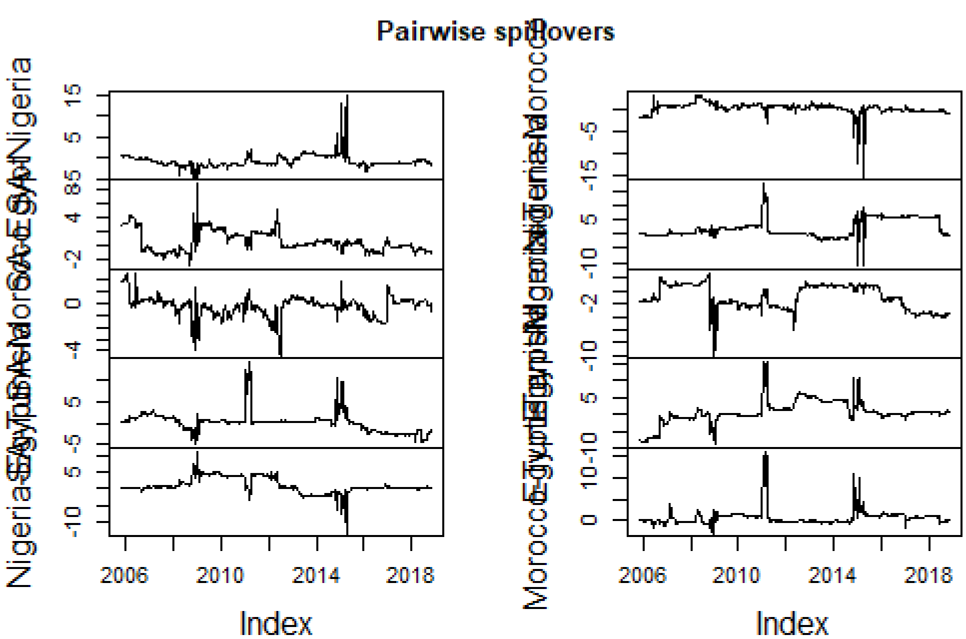


Figure 8: DY Volatility “Pairwise” Spillovers